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OPTIMIZATION OF CRIME CONTROL RESOURCES IN A SOCIETY

BY

STEVEN THOMPSON

A PLAN B PAPER IN PARTIAL FULFILMENT OF A REQUIRMENT FOR THE DEGREE
OF

A MASTERS OF SCIENCE

IN

ECONOMICS

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2011

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Abstract

OPTIMIZATION OF CRIME CONTROL RESOURCES IN A SOCIETY

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2011

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This paper looks at the economics of crime control through the Phillips-Votey Societal Cost Function model and mathematically proves that there is a socially optimal point at which society should be devoting resources towards the prevention of crime. This allows the society to minimize the social cost of crime given a theoretical cost constraint. This paper takes the model further by conducting comparative analysis to determine the effect that changes in the functional form of crime generation, and crime prevention will have on society as represented in the model. This paper also looks at the counter intuitive effect that growth in per capita GDP has a negative effect on crime rates, as a follow up to recently published article in *The Economist* magazine. We will expand this to see if this pattern continues for other countries with high rates of poverty. It also explores the social economical causes of crime generation by looking at Steven Raphael's paper *The Effect of Unemployment on Crime* and Richard Rosenfeld and Steven Messner paper *The*

Social Sources of Homicide in Different Types of Societies adding a multinational dimension to Raphael's paper. This paper expands the Messner and Raphael model by not only reproducing the OLS regression but by also using a fractional logit regression to create a more robust model. This paper uses the fractional logit regression in order to get a better idea how social economic factors such as unemployment rates and monetary inequality may influence crime.

This paper then looks at the largest portion of a state's expenditure of crime control, the use of prisons to see how effective they are in reforming prisoners and acting as a deterrent for future criminal behavior of this former prison population.

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Steven Thompson

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Existing Literature

The purpose of this paper is three fold, first to prove mathematically that there exists an optimal point for a society in which they should devote their resources to minimize the social cost of crime. The basis for the theoretical model comes from Llad Phillips and Harold Votey Jr. book The Economics of Crime Control (1981). Where Phillips and Votey create a model to explain crime control resources in a society, this paper will expand this model to allow for comparative analysis of Phillips Votey model. The Phillips Votey model was selected because it had the theoretical microeconomic construct that was conducive to allow us to look at both the cost created by the crime and crime resources. It is well accepted and frequently used in current literature and it allows the reader to achieve a greater microeconomic understanding of the entire effect of crime on society. Most other models look at the effect of the cost of the crime and not the cost and resources associated with crime control, the Philips Votey Model looks at both.

After showing the theoretical minimal point this paper will look at current crime control resource expenditures in the United States to see how those expenditures compare to the theoretical minimization point proven by this paper.

The Second point of this paper is to find the Social Economical causes of crime generation. Although the Phillips Votey model recognizes that social economical causes as an important source of crime generation, they do not explore

the social economic forces that drive crime generation, so this paper will use data from Liska, Chamlin and Reed's Article *Testing the Economic Production and Conflict Models of Crime Control* which looks at social inequality determined by both income inequality and racism as possible influences on crime. This paper will focus mainly on social inequality as well as with per capita GDP to see if that may be one of the reasons for the crime generation process. This paper will start by comparing the per capita GDP of two similar political structures (Republics, made up of three branches of government legislative, judicial and executive with the largest portion of power coming from the legislative branch and a law structure based on English common law) that have large portions of data available to the public to see how changes in per capita GDP may affect crime rates. The two countries we are comparing are India and the United States. This will show that as per capita GDP increases that both of these countries see an increase in specific types of crime, and that certain types of crime decrease in the United States with decreased change in per capita GDP, where in India those same crimes increase, we will explore why in this paper.

The third point of this paper is to explore utility model for a recently released prisoner in order to show how a society can allocate resources most efficiently towards decreasing the probability of recidivism. There have been a number of studies which indicate the effectiveness of prisons and causes of recidivism. Michael Jacobson in his book Downsizing Prisons: how to reduce crime and End Mass Incarceration (2005) argues that increased prison sentences do not reduce crime.

Joan Petersilia in her book When Prisoners come Home argues that there exists a number of aspects that effect prison reentry into society, housing, age at the time of the prisoner's release from prison, racism, inmate participation in prison programs, biases against prisoners to achieve employment, prior incarceration, use of the parole system, and drug treatment in prison. Lipton, Martinson and Wilks in their book The Effectiveness of Correctional Treatment: A Survey of Treatment Evaluation Studies conducted a meta-analysis which showed the effectiveness of supervision during the probation period, increased skill development, individual counseling, group counseling and Milieu therapy. This paper expanded these studies by creating a microeconomic model which shows how a released prisoner would optimize their utility given an economic constraint and how such optimization could result on recidivism depending on the utility and cost structure of our prisoner.

Introduction

In 2006 crime cost the average American at least \$344 either directly as a result of being a victim of crime or indirectly in taxes paid for crime prevention. One of the largest and seemingly most ineffective tools towards crime prevention in the United States is the prisoner reform system. In 1978, the United States spent \$5 Billion to operate the nation's prisons; this figured has increase in nominal terms by more than 1300% to \$72 billion in 2007. Increased spending on correctional facilities has caused a significant strain on the states, which on average spend 7% of their state budget on correctional facilities. As the demographics of the inmates are

changing, because of increased life spans and a growing part of the prison population with an age of 40+ years, this figure is predicted to increase significantly. The reason for this impending increase is because prisoners over 41 years of age on average cost the state \$66,000 a year, compared to \$22,000 for adults under 40, much of this cost is because of higher cost of medical cost. If the present nationwide rate of growth continues, it will be necessary to build the equivalent of two new prisons every week just to keep pace. Prior incarceration has been a poor deterrent for future violation of crime. According to the Bureau of Justice Statistics a person with a criminal history will be about 882% percent more likely to go back to prison than a person that was never previously incarcerated. (Statistics, 2007) (Jacobson, 2005) (Schmidt and Witte, 1988) (Bonczar & Beck, 1997)

Many crimes have a portion of the crime that has a measurable economic loss to the victim and to society. If a criminal burglarizes a victim, the victim has a fixed monetary loss as a result of the burglary, but there is also a non-monetary cost to the crime felt by the victim. The victim may feel less safe, increased fear, anger, or some other unwanted emotion as a result of the crime. The criminal would have some utility gain from performing the action, in the example above the criminal would receive an economic gain as a result of the burglary. This gain will likely come at some cost to the criminal, for example the time spent looking for people to burglarise could have been spent doing some other action to gain utility.

This paper would like to acknowledge the fact that not all crimes have a negative economic effect on society. Some crimes may actually have positive effects

on society for example Rosa Parks's refusal to change seats on a city bus, but for the analysis used in this paper it will make the assumption that the crime we are discussing has a positive effect for the criminal they gain some utility as a result of breaking the law, a negative effect for the victim(s) and the overall cost to society will be less than or equal to zero. This next portion of this paper intends to prove that there exist a cost minimizing point which will be most beneficial for a society in expending resources to prevent criminal activity.

Creating a metric for measuring the impact of crime rates on society

In order to make this model work a few assumptions and definitions need to be established; first crime in our model is defined as an act by some actor within society that is both deemed as a social bad, and that society is willing to allocate resources towards the prevention of said action. Second that crime is non-increasing with increased crime control resources (L), third with no crime control measures in place society would be at a suboptimal position. These assumptions are made because it reflects an optimal strategy in the real world. First if a society was at an optimal position with no crime resources expenditures it would signify one of two things; that the expenditures were redundant because no crime exists in the society, or that in each case crime control resources were used crime was always non-decreasing, this would mean that nothing a society could use would deter crime. The second assumption would mean that a society was not cost minimizers and hence not utility maximizes therefore the society would be irrational. The conclusion can be made that the total impact of crime on society is equal to the

impact of crime plus the resources used to deter crime. Llad Phillips and Harold L Votey Jr. in their book The Economics of Crime Control created a model for crime control. The variables are the following socioeconomic causal factors (SE), create a vector of m degrees of felony offenses (OF), m represents the specific type of felony offenses. Societal programs (SP) which are used to diminish the socioeconomic factors that create criminals, examples of these societal programs would range from transfer payments that help low income households, intercity youth leagues for at risk youth, or even the civilian conservation corps, intended to placate youth during economic hardships at the time of the Great Depression. The costs of the societal programs are indicated by $C_1(SP)$ this is born by society via the criminal justice system. (L) is a vector of resources used by the criminal justice system, L represents resources used for law enforcement and prosecution, e.g. police salaries, cost of prisons, and the purchase and maintenance of police vehicles. L is a (n) dimensional vector where n represents the number of resources available to prevent crime. The conviction ratio (CR) is a measure of the “certainty” of punishment, CR is seen as a deterrent along with the severity (SV), usually measured as the time of the sentence served. The cost associated with the severity is represented as $C_2(SV)$. Given a set level of felony offenses (OF), an increase in L would increase CR . Making the assumption that that more money spent on crime control given a fixed level of crime will result in more criminals being successfully prosecuted. (w) is the vector of cost associated with L . w is a n dimensional vector with each subgroup of cost associated with the corresponding subgroup in L , for example L^2 is associated w^2 , to illustrate

this point with a practical example lets assume that L^2 is an individual that could work as a police officer, w^2 would represent the forgone benefits to society losses to have that person stopping crime, so if he could have been a sculpture, w^2 represents the number of sculptures not made because the person was deterring crime. This paper make the further restriction that each good or service in L where 1 here represents the upper bound of the possible resources that could be used in crime prevention. Zero is the lower bound because we are assuming that there cannot be negative resources allocated to crime control using this and the assumption made before that 0 is a suboptimal solution therefore L represents the area allowable for an optimal solution we are insured that we have an interior solution. The crime imposes a cost to society either through the loss or damage of property, or through the cost in terms of loss of safety, later in this paper we will use a metric created to measure the loss in monetary terms. The loss rate (r) is the implied social costs. (r) is a vector of m values corresponding with OF . Thus the total cost to society (S) is calculated through the following formula:

$$S = rOF + wL + C_1(SP) + C_2(SV)$$

(Equation 1)

Figure 1 (appendix) is a reproduction of Llad Phillips, and Harold L Votey Jr. explanation of these variables which allows the reader to have a visual understanding of the variables. (Phillips & Votey, Jr., 1981)

The offense rate is a determined by a function of the conviction ratio, severity of punishment and socioeconomic causal factors (g) . Socioeconomic factors are

determined by a function of the offense rate (f)

$$\begin{aligned} \text{OF} &= g(\text{CR}, \text{SV}, \text{SE}) \\ \text{SE} &= h(\text{SP}) \\ \text{CR} &= f(\text{OF}, \text{L}) \end{aligned}$$

(Equation 2)

2. Increase social programs (SP)
 3. Increase the severity of punishment (SV)
- (Phillips & Votey, Jr., 1981)

We also make the assumption that the functions are quasi-concave. This assumption is created because of non-increasing returns to scale. If society is rational they will allocate resources on those resources that will have the largest economic benefit for crime prevention. Using this assumption we know that an optimal solution to this problem does exist.

Proof:

By creating a Lagrangian from equations 1 and equation 2 and taking the minimum

taking the first order conditions with respect to our choice variables OF, L, SV and SE gives you (and assuming that r and L are scalars).

Remember that g is the functional form of the offense rate, F is the functional form of the conviction ratio. From equation 3 we know _____ is negative and _____ is positive therefore the second term is negative, because it is subtracted it becomes a positive. We also know that _____ is negative. The left hand side of the equation is positive however, because both w^* and r^* are positive, therefore _____ _____) $\geq \text{abs}(\text{_____})$. And w^* becomes larger or r^* becomes smaller the difference between $\text{abs}(\text{_____})$ and _____ gets larger.

Removing the scalar assumption we have $[w] \bullet [r]^{-1} = \text{---} \text{---} \text{---}$

We know that the f function is convex because of the assumptions we made in the model which is sufficient to prove that this optimal point is a minimum or a set of points which constitute a minimum.

Using these assumption we have proven that there is an optimal point to which resources should be spent to minimize the cost of crime on a society.

We will now see how the model compares to the real world.

Determining r

As mentioned in the introduction it is very difficult to determine the loss a society incurs as a result of crime because the loss is not only monetary, but psychological as well. There have been a number of studies to try to express this loss in monetary terms alone. This includes the Wickersham Report, The President's Commission on Law Enforcement and Administration of Justice 1967, however for this paper we will use the Sellin Wolfgang measure. In 1964 Sellin and Wolfgang produced a study that is still widely used today to determine the monetary weights on a society. They conducted an extensive survey to determine the seriousness of a particular crime by asking survey respondents consisting of judges, police officers and university students to give a numerical value for the crime according to a list of 141 different crimes. If we combine their information with the President's Commission Report then we are able to gain some intuition regarding the real cost of offenses. This paper is reproducing the methodology for

finding the value associated with the Sellen-Wolfgang study and will later prove that the President's Commission Report is no longer a feasible option for obtaining the values for r . The Sellin-Wolfgang score for petty theft of \$5 has a mean magnitude scale value of 22.09, this score is 69.13 for larceny of \$5000 along that spectrum there is a linear relationship between the logarithms of the Selling Wolfgang Score and the dollar value loss. By using this Phillips and Votey were able to create a monetary value for each of the crimes listed in Sellin Wolfgang study, an example of that survey with their corresponding economic cost is found in the index of this paper. (Sellin & E., 1978) (Phillips & Votey, Jr., 1981)

Using this data we can create a measurement of our rOF value. We are able to do this by using data from the United States Department of Criminal Justice which keeps track of federal crimes prosecuted each year. We then are able to use the Phillips-Votey method for calculating social cost for the crime mentioned above. We can compare this cost for crime prevention, which we calculated as the average per person cost spent on the criminal justice program.

Although this list omits a number of less severe crimes that are subtracting from society; this study looks exclusively at: murder and non-negligent manslaughter, aggravated assault, property crimes, burglary, larceny and motor vehicle theft, now taking those values and standardizing them by using the consumer price index (CPI) to the 1993 cost level, and comparing them against the cost spent on crime prevention for 1993, 1997, 2000, 2003 and 2006 standardized them by using the 1993 CPI we are able to determine that the social cost of crime

decreases and at the same time spending on crime prevention increases. In this particular case $m=6$ If we multiply the probability of being a victim of a crime by cost associated with the crime we find that the total cost of crime is around \$252.71 the same individual would spend \$131 on crime prevention. In 1997 the social cost of crime was \$206.71 per person. The average cost for crime prevention was \$135.05. In 2000 the cost of crime dropped to \$171.99 and society spent \$150.21. In 2003, crime cost \$169.07 and society spent \$157.07 in prevention. In 2006 the cost of crime \$162.85, and prevention cost \$181.2 per person. Looking at the data it is possible to see that for every year the data is available in the United States, there has been a decrease in crime and an increase in crime prevention. Now the United States is spending more on preventing crime then the cost of crime is imposing on individuals in society. As long as we take the assumption that society is optimizing we can assume that the cost of crime is born by more than just the individuals impacted by the crime. There may be a number of reasons for this, people may be more aware of crime because of increased media coverage of crime, and so people not affected by the crime feel less safe with each crime committed because they are more aware of it (see appendix table 1 for data from original Sellin-Wolfgang study).

Comparison of Crime Control Resource Expenditure to Loss Due To Crime					
Year	1993	1997	2000	2003	2006
Crime Control Resource Expenditures	\$131	\$135.05	\$150.21	\$157.07	\$162.85
Loss Due to Crime	\$252.71	\$206.71	\$171.99	\$169.07	\$181.2

Total Cost to Society	\$383.71	\$341.76	\$322.20	\$326.24	\$344.05
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(CPI provided by United States Department of Labor)

Obviously with a fixed cost of crime control resources and decreasing crime we would expect that the United States would not increase spending on crime control. This paper will now look at possible causes of this seemingly irrational behavior.

Hypothesis: The Value of Life has increased faster than inflation

The possible explanation for this would be an increase in the value of a human life. Recall the Sellin Wolfgang study used the presidential commission report which created a value of statistical life (VSL) to create the monetary cost of homicide. There has not been a reproduction of the VSL by a presidential commission report since the 1967 study, but there have been a number of studies conducted since that time from various federal agencies. The Environmental Protection Agency in their report *Regulatory Impact Analysis (RIA) for Existing Stationary Compression Ignition Engines* changed their VSL from 6.3 million to 9.1 Million, well above the changes because of inflation to the determined value of life in the value of life study in the Presidential Commission. The Food and Drug Administration also increased the VSL from \$5 million in 2008 to 7.9 million this year. And the Transportation department increased the VSL from \$3.5 million to \$6.1 million. This shows that a number of federal agencies have increased the value of life during that time. With an increase at the top of the Sellin Wolfgang measurement, recall that the Sellin Wolfgang used the value of life created by the

presidential commission to determine what the value of murder is, the cost of crime would increase throughout the entire spectrum of values. (Sinha, Depro, & Braun, 2010) (Appelbaum, 2011)

Understanding SE

Throughout much of the literature regarding crime generation and crime control, many authors point to a black box of social economic factors having a large impact on crime generation. Phillips and Votey point to it directly as the single cause of crime generation (see figure 1 appendix), but there has been little said about the specifics of the social economical cause for crime generation. One possible explanation is that people are driven to commit crime out of desperation, and if a society increased its resources to members of its society then that society would have fewer members causing crime, because of decreased competition for those resources. The reasoning behind this hypothesis is as follows, with increased resources of normal goods received by an individual the marginal demand for that good diminishes, if the marginal benefit of the item is high then the marginal cost a person is willing to pay increases. If we assume that we can monetize societal punitive measures such as a prison sentence, and the perceived odds of a person getting caught (and assuming that the individual is risk neutral and does not need increased incentives to participate in the action). The cost of the act would be the cost associated with the punitive measure multiplied by the chance of getting caught. This may be an economically viable solution for a criminal in a Jean Valjean situation in which an individual marginal benefit for stealing bread (life for him and

his family), but in which resources are plentiful and the cost of not stilling the bread is missing a meal as opposed to starving to death the individual may not be willing to take the risk because the marginal benefit is lower. This would lead us to believe that decreased per capita GDP would cause increased crime.

The Economist presented evidence, at least in the United States of decreased crime rates associated with decreased GDP for the past recession. In order to find the impact that per capita GDP has on crime, this paper looked at a data set of per capita GDP produced by the University of Pennsylvania to make my calculations of changes in crime with regards to the percentage change in GDP. This paper looked at crime rates in both India and the United States to determine the effect that the annual change in real GDP has on crime rates. The author of this paper chose those two countries because of the robust internal data set that they collect and because they represent a developed nation along with a developing nation. This is important to see if there is a point, possibly after all of the basic resources (food, shelter, and water) have been met that an individual is not influenced by the desire to break the law in order to meet the high marginal benefits that the increased resources will allocate to that person. These two countries have many similarities, they have representative government, they both have a similar legal system with the basis of the law being common law. They both have the same three branches of government. And although they have a few parts of their society that are different (e.g. caste system, legal corruption) the most significant difference is poverty rates. Comparing these two countries allows us to determine whether a country with a

high level of poverty has the same response to that of a country with low levels of poverty (poverty being defined as an annual income of less than 3000 a year). The Bureau of Justice Statistics provided data for the crime rates in the United States. The data for India is derived from the National Crime Records Bureau. (The Economist Online, 2011) (Heston, Summers , & Aten, 2011)

When performing the OLS regression of crime with respect to change in per capita GDP, normalizing GDP in 2007 terms we find that in the United States when we run a normal OLS regression we get a coefficient of .09, but the adjusted R^2 is only 0.0389 if we make an adjustment to fractional logit model it becomes 4.52 with a std error of 2.62. This becomes significant at the .1 level, but our Adjusted R^2 decreases. This shows very weak evidence that increases in the change of per capita GDP increases crime.

Table 2 Fractional logit regression of total crime on change in GDP in U.S.A.

Coefficient	Estimate	t value	Pr(> t)
Intercept	-.3190 (.1702)	-1.848	.0670
Change in GDP	4.5211 (2.6249)	1.722	.0914

Adjusted R^2 0.03859

Table 3 Fractional Logit Regression of Burglary on change in GDP in U.S.A.

Coefficient	Estimate	t value	Pr(> t)
Intercept	-.8412 (.2428)	-2.365	.00112
Change in GDP	15.2854 (3.7441)	4.082	.000168

Adjusted R^2 0.2423

Table 4 Fractional Logit Regression of Murder on change in GDP in U.S.A.

Coefficient	Estimate	t value	Pr(> t)
Intercept	-.0574 (.0049)	11.675	.0000
Change in GDP	.2863 (.0759)	3.772	.0004

Adjusted R² 0.2125

When this paper look at violent crime it saw that the change of per capita GDP using an OLS regression gives us a negative coefficient of -.0059 but the adjusted R² is .0031 and the coefficient is not significant so there should not be any conclusion drawn from this regression. The fractional logit regression shows a still negative coefficient, but the adjusted R² is negative so there does not seem to be any relation between change in per capita GDP and violent crime.

When this paper look at crime with a possible monetary gain it reported that OLS regression gives us a coefficient of -.0017 with a standard error of .008 but the adjusted R² is negative so we cannot find any correlation there. We get similar results with our fractional logit regression, it seems as though there is no correlation between monetary crime and changes in per capita GDP.

Although the relationships between monetary crimes and change in per capita GDP seem spurious, this paper is able to see a few significant sub categories of nonmonetary crime. When we perform a fractional logit regression on the per capita burglary on per capita change in GDP we can see that it is positive at a significant level. This suggests that as the rewards from burglary increases because people have more money, because of these increased rewards criminals will be

more likely to rob. Property crime also increases with increased GDP. When we look at murder we also see strong evidence that changes in per capita GDP effect murder. The Adjusted R^2 was .1773 and was shown to be significant at 99%. This suggests that increases in per capita GDP causes murder to increase. This allows us to gain some insight into the cause of the spurious relationship between the changes in per capita GDP and changes in monetary crime. The subcategories that have the largest effect on the regression theft had spurious results when it was regressed against changes in GDP. From the data this paper used in the United States overall crime seems to be spurious with changes in GDP but certain subsectors of crime (i.e. burglary and murder) increase with increase GDP.

Quantifying the results in India is a little more difficult because we are looking at IPC (India Penal Code) level crime or crime that is prosecuted at the national level, there have been a number of crimes that have become classified IPC in the last 50 years. This effects our model in two different ways first it increases the total amount of crime committed after the new classification is determined second some of the crimes that were characterized as one type of crime or placed in the Other IPC crime category now have a new placement which causes sudden shifts in the subcategories when we incorporate the new category. For example setting fire to somebody's house in India in 1970 may have been considered as part of riot, murder, other ICP or just prosecuted at the Local and Special Law level (LSL) which is basically the provincial level in 1970, but when Arson became a category in the ICP in 1995 it pulled from all of those categories depending on how the criminal

justice system found would be the most advantageous way to prosecute the crime. In an effort to correct for this this paper will look at crime at the larger scale of monetary and nonmonetary gains. This should mitigate the effects caused by pulling things across categories, but it does nothing to ameliorate the effect of pulling crimes from LPL to IPC. So this paper will also look at a few subcategories that have information for a larger period of time are affected less by the introduction of a new category (i.e. murder, counterfeiting and rape). (National Crime Records Bureau, 2009)

Running the regression from 1972 to 2009 allowed us to get results from our OLS regression of -3.786×10^{-4} which suggests that we have a negative coefficient our standard error is 3.267×10^{-4} and our R^2 is .0094 which is rather low as well. When we use a fractional logit model with $v = .003$ (v represents the upper limit to the model, the definition of v for the fractional logit model is defined better in the next section for readers not familiar with the variables defining the fractional logit model) we get a model that shows that our coefficient is negative and it is not significant at any level. Our R^2 is still very low at .011. In an effort to get more accurate results we will look at murder and burglary by themselves to determine if change in GDP has an effect on crime. This result is likely from the change in classification of the data.

When we look at murder and burglary alone we find using a fractional logit model again that increases in the change of GDP decreases murder this finding is significant at the 99% the standard error is .697 so unlike in the United States

periods of increased economic growth causes Indians to kill less not more. When we run the fractional logit model with burglaries we find the same thing as in the United States. Burglaries increase with positive changes to real GDP. Therefore widespread poverty is likely not the cause of burglary, more likely the financial reward resulting from the burglary is the cause of burglary.

Table 5 Fractional Logit Regression of crime on change in GDP in India

Coefficient	Estimate	t value	Pr(> t)
Intercept	.0019 (.0000)	82.926	.0000
Change in GDP	-.0004 (.0003)	-1.159	.2550

Adjusted R² 0.0097

Table 6 Fractional Logit Regression of burglary on change in GDP in India

Coefficient	Estimate	t value	Pr(> t)
Intercept	-.4141 (.1408)	-2.941	.0059
Change in GDP	-.0004 (1.9957)	2.451	.01955

Adjusted R² 0.1251

Table 7 Fractional Logit Regression of murder on change in GDP in India

Coefficient	Estimate	t value	Pr(> t)
Intercept	-.0067 (.0492)	0.136	.8923
Change in GDP	-1.6623 (.6978)	-2.382	.0229

Adjusted R² 0.143

Expanding the model internationally

From equation 2 we were able to determine $\frac{\partial OF}{\partial SE}$ where g is the functional form of OF . Because r is fixed see appendix table 1 and $S = rOF + wL + C_1(SP) + C_2(SV)$ (equation 1) and $SP = h(SE)$. It is important to determine SE which will have the largest effect on OF resulting in the lowest S possible. So we need to determine what aspect within SE which would cause the largest change in $\frac{\partial OF}{\partial SE}$.

Because the objective is determine the universal social economical causes of crime, this paper needed to find a criminal offense that would be determined in a similar manner in each of the criminal justice programs, was legally defined in each country as nearly the same thing, and for which we would be able to derive universal statistics. The best crime for that is murder. Unlike other crimes it is universally described in the same way. Also unlike other crimes which end up going unreported at a higher degree if the victims do not believe that the criminal justice system will produce results, murders unlike a number of white collar crimes are highly noticeable and visible. It has the added benefit of representing the largest price vector in r , which would make it a strongly correlated with rOF . This paper would like to acknowledge the fact that extracting data from many different sources may cause a bias in the data. This paper attempted to mitigate the bias by extracting my data from a single source. The United Nations keeps track of all murders; they extract this data from the World Health Organization, Interpol, and the host countries crime reporting agencies. Because these sources were not always the same this paper used reports from the World Health Organization first, followed by the any other international organization, if that was not available, this paper used

domestic data, this paper would like to acknowledge the fact that when all three data sources were available there existed slight variations between the sources. The United Nations had only has available data from 2003 on, this caused a limit to the sample size. Having stated this, the data analyzed in this paper still has a robust sample size consisting of 290 different samples. Any regression conducted may have omitted some of the data if the independent variables were not in our dataset.

In order to determine the coefficients which have the largest impact on crime generation we need to look at existing models and theories. Rosenfeld and Messner in their paper, the *Social Sources of Homicide in Different Types of Societies* were able to extract from the existing literature the leading causes of homicide. A large amount of the existing literature looks toward inequality leading to a large level of lethal violence. The argument is that as inequality increases in a society there is a large divide that separates the decision makers from the masses. The law is therefore ineffective for protecting the masses and so they often take punitive measures themselves. He later states that Knauff has found that simple societies (smaller less developed societies) which are extremely egalitarian often have similar acts of aggression because of the low likelihood of other punishment occurring from a government actor. The other aspects that effect homicide are disorganization measures, things that cause sudden changes to moral codes or even population density. He also hints at the possibility of envy by the people less wealthy masses. Another aspect that Rosenfeld and Messner mention that may have an impact on crime are complexity measures such as political authority,

judicial authority, and organizational complexity. This reasoning for this is similar to that of the inequality aspect, Rosenfeld and Messner state that determines whether or not the members of the society believe that the society has the ability to take punitive actions against offenders. If they do not believe that they do then it is likely their criminal justice system will take action against criminals they will do so themselves. One interesting aspect to consider here is that when an individual and not a society is to extract criminal justice by themselves it almost invariably results in afflicting pain or death on the criminal. The reason for this is because the cost to the individual seeking justice would be too large for any other means. (Rosenfeld & Messner, 1991)

Steven Raphael presented data which indicated that unemployment decreases the amount of crime, but violent crime increases because of decreased employment. Raphael used a normal OLS regression to create these findings across the United States, and then performed a two stage least square to indicate the effect that crime has on unemployment. This paper will reproduce the study across all nations, but because the OLS regression is not an ideal regression across this data (the dependent variable only deals in the positive realm and the dependent variables also are not continuous (\mathbb{Z}_n^+). There cannot be a negative number of murders or even 1/3 of a murder). This may be the reason for the low R^2 results from the Raphael paper. In an effort to correct for this, this paper used a fractional logit model. By doing so the resulting coefficients have a loss of accuracy, but we are able to better determine whether or not an independent variable has a positive or

negative effect on the dependent variable with more accuracy than with the OLS regression. (Raphael & Winter-Ebmer, 2001)

The linear form of the fractional logit model used in this paper is $\ln(Y/(v-Y)) = \beta'X + U$, where v is the upper bound of the dependent variable. The dependent variable is murders per 100,000 people the obvious upper cap would be 999,999; but that would not constitute a good upper bound, because it is beyond the scope of realistic estimates. A more accurate upper bound for these societies with regards to the homicide rate is 80. If we look at our dataset it becomes clear as to the reasoning for the rate. Obviously 80 murders per year is well above the highest amount in the data set, but looking at the data set 80 is still a feasible number, it also allows for some of the higher data sets to have a positive coefficient. This is important because it allows us to gain some efficiency because after the data manipulation the fractional logit model is increasing its R^2 through turning into an OLS regression. The obvious shortfall is that because we are using a fractional logit model we will have estimators with little to no meaning they are not the coefficient that fit the model, the most important aspect that we are determining is the sign of the estimators. Also because the outliers have a significant effect on the model countries like Columbia have a large effect on the regression (see figure 2 appendix) the author of this paper considered omitting these data points because of the strong impact they have on the model but decided against it because it would bias the model. This paper just want the reader to be aware of this point.

Results of our model

In order to test to see if Rosenfeld and Messner were correct when said that monetary inequality has an effect on our model, this paper used the Gini coefficient determined by the World Bank as an independent variable. This paper selected the Gini index as a measure for inequality because it shows the distribution of consumption, the lower the coefficient the more egalitarian the society. Then the author of this paper averaged the murders by all of the years available for that country. Figure 3 (appendix) was the result. The data looks as though as the Gini coefficient increases murder increases as well. This means that as a country becomes less equal in their distribution of wealth, their rate of murder increases. With an OLS regression we get a coefficient of .8103 and a standard error of .1458. R^2 is .374 it is significant at the 99.9% level. When we use fractional logit model we get a positive coefficient at the 99.9% level as well which shows strong evidence showing that this coefficient is positive.

Table 8 Fractional Logit Regression of murder on Gini Index Worldwide

Coefficient	Estimate	t value	Pr(> t)
Intercept	-23.2552 (5.6206)	-4.138	.0001
Gini	-.8103 (.1458)	5.556	.0000

Adjusted R^2 0.374

When we look at the legal system of each country we are able to gain an idea of the effectiveness of their judicial system. Using the Economist Intelligence Unit to look at the legal and regulatory risk factors, we are able to obtain an overall picture of how their judicial system works. The Economist Intelligence Unit ranks the legal

system according to how “fair” their judicial system is. The higher the number the more corrupt it is. The Economist Intelligence Unit looks at how likely a person is to get an impartial trial, how likely a person is able to avoid prosecution because of people they know, or the individual’s influence from their wealth. It also looks at the likelihood of a person going to jail because of political retaliation. When we run a fractional logit model on this we see that the Gini index is still significant and that the Economist Intelligence Unit’s assessment of legal and regulatory risk is also significant at the 95%. By combining the two we get an adjust R^2 of .4498.

Table 9 Fractional Logit Regression of murder on Gini Index and legal risk worldwide

Coefficient	Estimate	t value	Pr(> t)
Intercept	-7.1822 (.0948)	-11.061	.0000
Gini	-.0948 (.0175)	5.418	.0000
Law	.0120 (.0060)	2.009	.0503

Adjusted R^2 0.4498

This finding suggest that Rosenfeld and Messner were correct the higher the inequality and the higher the less efficient the judicial system the higher the murder rate. (See appendix for econometric coding using R)

Looking at Steven Raphael’s paper when this paper replicated his OLS model utilizing a fractional logit model, and expanding it to cover 49 countries this paper was able to still obtain a positive coefficient with regards to the unemployment coefficient, this suggests that the coefficient is truly positive and that unemployment does cause murders to increase. This is significant at the 99.9%.

Table 10 Fractional Logit Regression of murder on unemployment, inequality, and legal risk worldwide

Coefficient	Estimate	t value	Pr(> t)
Intercept	-4.227 (.1633)	-22.885	.0000
Unemployment	.1350 (.0180)	7.517	.0000

Adjusted R² 0.164

In an effort to make the model even more robust, this paper combined both Raphael's and Rosenfeld idea to see what would happen if we perform a fractional logit model to look at the effect that inequality, unemployment, and judicial and regulatory instability would have on the murder rate. Because the World Bank is sporadic about collecting data to create the Gini Index this paper was able to create its own measure of inequality. The design of my inequality index is quite separate from that of the Gini index, where the Gini index creates a number based on the inequality of consumption, my index is based off the idea that the larger the deviation from the income class that hold the majority the higher the number. So if there is a society with a large number of households in one income group and another large portion of a society in a much more affluent income group, whereas the political elites in the higher income group would likely have more influence in law making and implementation, this country would have a very high inequality value. For example apartheid South Africa would have a very large inequality value, where as a country that was more or less in the same income group such as Indonesia or the Czech Republic would have a low inequality value. This value already has transfer payments included. When this paper ran that regression it find

that unemployment is significant at the 99.9%, as well as legal and regulatory risk, both of those coefficients are positive. Inequality is also positive, but only at the 95%. The R^2 value is .3395.

Table 11 Fractional Logit Regression of murder on unemployment, law and inequality worldwide

Coefficient	Estimate	t value	Pr(> t)
Intercept	-5.427 (.0367)	-14.881	.0000
Unemployment	.0959 (.0021)	4.586	.0000
Inequality	.0001 (.0001)	1.661	.0984
Law	.0269 (.0043)	6.314	.0000

Adjusted R^2 0.3395

This finding shows evidence Raphael, Rosenfeild and Messer were right even if we expand our study across multiple countries and we use the fractional logit model. This evidence suggest that social economical programs that use transfer payments to make society more monetarily equal and programs that increase employment could be used to decrease the murder rates world wide.

Effectiveness of Prisons

A significant portion of the prison population is repeat offenders. There is a 50.1% chance that a released prisoner would be return to prison within 3 years. By reducing the amount of recidivism states have the opportunity to retard this mounting demand for prison space. A number of costly measures are available to decrease the likelihood of recidivism among prison populations. But the costs are prohibitive, so in order for these programs to have the largest effect, a number of

federal and local organizations have looked at the characteristics of inmates most at risk of recidivism in order to allocate resources in the most effective manner possible. In this portion of my paper we will look at the static characteristics of the inmate population released in 1978, and attempts to isolate the characteristics of prisoners who are most likely to return to prison. (Statistics, 2007) (Jacobson, 2005).

Using data collected from the North Carolina Prison system in 1977-78 and again in 1979-1980 by Schmidt and Witte (1989) we are able to gain some intuition as to the effectiveness of the prison system. Although this data is rather dated it encompasses the most robust study this author could find with regards to the effectiveness of the modern prison system.

The variables, selected by Schmidt and Witte, are not open to interpretation and therefore difficult to manipulate. These variables are static by nature; a one-time look at the conditions a prisoner is facing at the time of his/her release. These models can easily be carried over across studies because they are almost universally defined in the same manner.

This data included all inmates released between the periods of 1977 to 1978 and 1979 to 1980. It included 9457 individuals, but only 8849 are not missing information. Listed in the next section of the paper are the variables and their definitions

White: A dummy variable equal to one for any race (including Oriental, Hispanic, Native American) that is not of African descent.

Alchy: A dummy variable equal to one if the inmate's record indicates a serious problem with Alcohol.

Junky: A dummy variable equal to one if the inmate's record indicates a serious problem with hard drugs.

Super: A dummy variable equal to one if the inmate's release was supervised (he/she was release on parole).

Married: A dummy variable equal to one if the inmate was married at the time of his/her release.

Felon: A dummy variable equal to one if the inmate was in prison for a felony.

Workrel: A dummy variable equal to one if the individual participated in the work release program during their sentence.

Propty: A dummy variable which is equal to one if the crime committed was a crime against property.

Person: A dummy variable equal to one if the crime committed was against a person (the crime could have been against a person and property in which case both this variable and propty would be one).

Male: A dummy variable equal to one if the inmate is a male.

Priors: The number of previous incarcerations not including the sample prison term

School: The number of years of formal schooling completed

Rule: The number of rules broken by individual during their sentence

Age: The age (in months) of the inmate upon release.

Tservd: The time served (in months) of the sentence

Recid: A dummy variable equal to one if the individual returned to jail within the follow up period (three years)

Time: The amount of time from one the person was release to the point at which the person returned to prison. If the person did not return to person within the three years examined this variable is equal to zero.

There are a number of possible variables listed above that may be correlated, this paper will address the issues here and explain what it did to decreased the multicollinearity problem in order to get a better R^2 . It is safe to believe that $Tservd$ and Rule would be correlated because the longer a person is in prison the more likely they are to break more rules the author of this paper divided rule by $Tservd$ in order to make it rules per month. This allowed us to normalize the number of rules broken to be uncorrelated with how long a person was in prison. This paper also tested correlation between age and marriage, this was not statistically significant.

Hypothesis

In order to understand the reason for recidivism across these variables this paper created a constrained incentive structure.

$$\begin{aligned}
 & \text{Max } U(v(\pi(s,i,r)), w(\pi(s,i,r)), \beta A_{t+1}(p,u)) \\
 & \quad i,r,s,e \\
 & \text{S.t. } \bar{E} = g(s,e,d)v(\pi(s,i,r))E[f(p,u)|A_{t+1}] h(p) \\
 & \quad + w(\pi(s,i,r))E[c(k,e,p,r)|i,u]E[f(p,u)|A_{t+1}] \\
 & v_{\pi} \geq 0, v_{\pi\pi} \leq 0, \pi_s \geq 0, \pi_{ss} \leq 0, \pi_i \geq 0, \pi_{ii} \leq 0, \pi_r \geq 0, \pi_{rr} \leq 0, w_{\pi} \geq 0, w_{\pi\pi} \leq 0, g_s \leq 0, g_{ss} \leq 0, g_e \\
 & \geq 0, g_d \geq 0, g_{dd} \leq 0, c_h \geq 0, f_p \geq 0, f_u \geq 0, A_p \leq 0, A_u \leq 0, h_p \geq 0, c_e \leq 0, c_p \geq 0, c_r \geq 0
 \end{aligned}$$

(equation 4)

I will breakdown the reasoning behind the functional form of this model in the next section, in this section this paper will concentrate solely on introducing the parameters. This model suggests that an inmate is attempting to maximize their utility (U) which is a function of the utility derived from the legal profits (v) and illegal profits (w), along with the discounted utility derived from their next period level of freedom (A_{t+1}) in our model this will be simplified to either free or in prison, but this could theoretically allow for a person on probation, or under alternative forms of incarceration such as house arrest. A_{t+1} is a function of priors (p) and amount of crime the criminal is engaged in (u). This paper also assume that profit is modeled by the level of legal skills a person possess (s), such as literary, quantities and technical skills, in our model this paper will use amount of schooling to be a proxy for this, the amount of illegal skills a person has such as fraud, scamming, and hacking (i), and the level of risk a person is willing to engage in (r).

Next this paper created a constraint in the level of effort a person in willing to engage in, this constraint could represent how many hours that person works in a day (E). The constraint is made up of the disutility function derived from using effort to gain money (g), this disutility function is a function of the level of effort put forth (e), the level of schooling an individual has (s) and the amount of discrimination which exists for the individual(d). This is multiplied by the amount of utility from legal profits, and then multiplied by the expected value family function this condition function is conditional on the value in the next period's

situation ($E[f(p,u)|A_{t+1}]$). This is then multiplied by the housing function which is a function of priors ($h(p)$).

The next aspect of our model is the associated cost function of illegal activities, which is the expectation of their chance of getting caught conditional on the amount of illegal activity the criminal is pursuing and the level of illegal skills the criminal has ($E[c(k,e,p,r)|i,u]$). This paper assumes that the expectation of the chance of getting caught is a function of hubris, effort, priors, and level of risk the individual is engaging in, multiplied by the expectation of the family function in the next period.

Intuition for expected signs and magnitudes of parameter estimates

The model was created through interpretation of possible utility functions derived from explanations of criminal activity given by existing literature. First it is important to separate the utility derived from the legal utility function and the illegal utility function in order to create a separate cost function, but the profit obtained from the two different activities may be different as well.

Some criminals gain utility from the excitement of breaking the law. At the same time some criminals may feel guilty for breaking the law. Because of this this paper assumes that criminals would have different utility function derived from two different profit making activity, and this value may be different even though they obtain the same amount of profit. In both of these cases this paper expects that the first derivative of the profit function would be positive. The third aspect of the utility function is their state of being in the next period; the main purpose of prisons

is to be punitive. Because this paper is looking at a static optimization problem, this paper assumes that the amount of prison time the individual faces in the next period would cause a decrease in utility. The amount of time the person faces is determined by two different aspects; the type and amount of crime the criminal is convicted of, and with the introduction of the three strike program (a program that significantly increases punishment for criminals that have two previous crimes), the number of prior convictions. This would cause A_{t+1} to be negative in both u and p .

The reason why the cost function incorporates the family is because the expected cost from the family function associated with legal activities may decrease the cost associated with pursuing legal profits. The Vera Institute of Justice found that

"families provide critical support early on... [recently released prisoners] received financial support from them as well. Family members helped to locate work and encouraged abstinence from drugs and compliance with treatment...Offenders whose families accepted and supported them also have a higher level of confidence and were more successful and optimistic for their future."

So if in the next period the individual is free then this paper expects that the family function would have a value between 0 and 1 which would decrease the overall cost function associated with legal profits. (Petersilia, 2003)

The family function also may increase the cost function associated with the illegal activity value function this is very prominent with female prisoners. Lipsey and Derzon found that the separation of a mother from her child was cited by the mother to be one of the most difficult aspects of imprisonment. This would suggest that if a person is expect in the next period to be separated from their family

because they are participating in crime that the family function would add to cost making it a value greater than one. (Petersilia, 2003)

The reason why the effort utility function incorporates discrimination is because many professions discriminate against former prisoners.

“There is a serious stigma attached to a criminal history – particularly a prison record in the legal labor market, and ex-offenders are often shut out from legitimate jobs. Surveys of employers reveal a great reluctance to hire felony offenders...Even if ex-prisoners are able to find a job there is a substantial impact on future earnings (about 30 percent lower), and firms willing to hire ex-offenders tend to offer lower wages and fewer benefits” (Petersilia, 2003)

This would suggest that partial derivative of g with respect to d would be positive.

Housing also affects the cost structure of the legal utility profit function. Many ex-prisoners experience a very difficult time finding suitable housing. Because of parolee restrictions they are often not able to live with family and friends that have any criminal history. They have an extremely difficult time finding any type of private housing because apartments require first and last month's rent plus a security deposit. And when prisoners are release from prison they usually do not have any money. While private housing represents 97 percent of the total housing stock, a person still can try to obtain public housing, but most providers are required to deny public housing to felons. This results in a large portion of former prisoners to become homeless. The Bureau of Justice Statistics estimates that 12 percent of prisoners are homeless this becomes an issue because it decreases the chance of employment and reintegration into society. A study by Bradley et al suggest

“Housing is the linchpin that holds the reintegration process together. Without a stable residence, continuity in substance abuse and mental health treatment is compromised. Employment is often contingent upon a fixed living arrangement.” (Petersilia, 2003)

This would lead us to believe that the partial derivative of h with respect to d would be positive.

As this paper examines the effort utility function it see that it is a function of skill, effort, and discrimination. The reason why discrimination is included is because it can have a large impact on the effort disutility function. This would cause the partial derivate of d with respect to g to be positive.

“[race] affects every aspect of reentry; including communities labor markets, family welfare, government entitlements, and program innovations, which need to be culturally appropriate” “20 percent of black males will experience a prison term before reaching age 35.” (Petersilia, 2003)

The reason why this paper included the s inside the g function in the effort function is because low skill labor is usually associated higher levels of manual labor. But s also affects both the profitability of legal and illegal activity. Finally this paper has discounted value of next periods punishment multiplied by the chance of getting caught as part of the cost function associated with illegal profits. We would expect that the chance of getting caught would be determined by the person’s level of illegal activity and skills associated with performing illegal activities. Because this is an expectation operator we will expect that k which is the value inside of the chance function associated with hubris. This would cause the partial derivate of c

with respect to k to be negative. But when you look at risk as a function of the chance function you would expect that the partial derivative to be positive.

Test statistics and conclusions from the hypothesis

From the theoretical model presented above our hypothesis is that the utility structure for a normal prisoner would look like

$$\text{Max } U(v(\pi(s,i,r)), w(\pi(s,i,r)), \beta_{A_{t+1}}(p,u))$$

$$\text{S.t. } \bar{E} = g(s,e,d)v(\pi(s,i,r))E[f(p,u)|A_{t+1}] h(p)$$

$$+w(\pi(s,i,r))E[c(k,e,p,r)|i,u]E[f(p,u)|A_{t+1}]$$

This would mean that we would have evidence that supports this model if Rule and Male were determined to be positive, and white, married, and school were negative because they have the largest one-sided effect on our model. This paper would also expect that priors, T_{served} would be near zero, or not significant because they are influenced by both sides of the model.

Because this paper is working with a dichotomous dependent variable this paper ran a probit and logit regression on the 1978 cohort in order to determine the likelihood of recidivism. The Logit test achieved a higher prediction rate. The coefficients of our logit model are listed in table 2. Of the variable listed in table 2 the only ones that are significant at the 99% level are white, alchy, male, married, person, priors, school, rule, age and t_{served} . Here is a table of the respective coefficients. Note that because we ran a logit model the coefficients are most important by telling the direction of the impact, if the coefficient sign is positive it

has a positive it increases the likelihood of a criminal returning to prison, if it is negative it decreases the likelihood.

Table 13 Results from Logit Regression 1978 Cohort

***Rule	***Male	***Alchy	***Priors	TWorkrel	Junky	*Tservd
1.4354 (.3454)	.6301 (.1609)	.5648 (.0838)	.1675 (.0155)	.1283 (.0692)	.0727 (.0746)	.0179 (.0020)
Super	***Age	***School	Propty	*Married	*Person	*White
.0001 (.0750)	-.0046 (.0004)	-.0527 (.0147)	-.1141 (.0836)	-.1585 (.0788)	-.3190 (.0788)	-.5281 (.2727)

standard errors denoted in parenthesis.

*** indicates that is significant at .001 level, * it is significant .05 level, t it is significant at .1 level

You can use these coefficients to compare against my model.

$$\text{Max } U(v(\pi(s,i,r)), w(\pi(s,i,r)), \beta A_{t+1}(p,u))$$

i, r, s, e

$$\text{S.t. } E = g(s, e, d) v(\pi(s, i, r)) E[f(p, u) | A_{t+1}] h(p)$$

$$+ w(\pi(s, i, r)) E[c(k, e, p, r) | i, u] E[f(p, u) | A_{t+1}]$$

$$v_{\pi} \geq 0, v_{\pi\pi} \leq 0, \pi_s \geq 0, \pi_{ss} \leq 0, \pi_i \geq 0, \pi_{ii} \leq 0, \pi_r \geq 0, \pi_{rr} \leq 0, w_{\pi} \geq 0, w_{\pi\pi} \leq 0, g_s \leq 0, g_{ss} \leq 0, g_e$$

$$\geq 0, g_d \geq 0, g_{dd} \leq 0, c_h \geq 0, f_p \geq 0, f_u \geq 0, h_p \leq 0, A_p \leq 0, A_u \leq 0, h_p \geq 0, c_e \leq 0, c_p \geq 0, c_r \geq 0$$

The first coefficient, rule, is positive so it increases the likelihood of a person going to prison; it is also our best proxy for the w utility function, because it shows the willingness that a prisoner has to break the law in order to get what he wants inside of prison, this should also correspond to the willingness to break the rules to achieve gain outside of prison. So as the weighted value of this utility function is

high relative to the v utility function you would expect that the person would break the law more often than someone with a lower w utility function, this would likely cause the person to be arrested and thus increase recidivism. The next highest positive coefficient is male, but to understand why this coefficient has such a high value relative to the other variables we will look at it in terms of why being female would cause a negative coefficient. If you recall from above one of the most difficult aspects of prison for females is the separation from young children, this will increase the cost function associated with $E[f(p,u)|A_{t+1}]$ in the illegal activity side because the A_{t+1} would likely correspond to being in prison, this would have a larger effect on most women than most men. Because the cost function is higher with regard to utility gained from illegal activity you would expect a significant shift of women with young children to the legal side. The model does not examine the utility structure associated with vices, so won't try to fully explain the impact that alchy and junky has on our model, however, it is likely that the discount function (β) increases therefore the punitive aspect associated with next period may not matter as much as this moment's benefit from participating in drug use. This analysis is only relevant, however, in cases dealing with the use or pursuit of drugs. The next largest positive coefficient is priors. This affects a few different areas, because priors affects the disutility portion associated with our A_{t+1} function You would expect that portion to decrease future crime involvement, but at the same time it would increase our i function. Petersillia explains why the i function would be affected in her book *When Prisoners come home*.

“Criminologists have long suggested that prisons breed crime, act as schools for criminal learning, and produce a variety of criminogenic effects. People who serve time in prisons often return home with stronger ties to other criminals, greater criminal skills, and more antisocial attitudes... imprisonment may actually serve to increase overall levels of crime in the community. “

Because λ affects the profit function associated with illegal skills, and decreases the chance of getting caught, therefore, lowering the cost function utility from illegal activities this would cause the ex-prisoner to shift to illegal activities. On top of that is a third aspect outside our model criminals have lower life spans, and because they die at a younger age, they have less opportunity to commit crime. Because priors affects both disutility from committing crime and decreased cost of committing crime you would expect that the coefficient would be low, and the model does not predict the sign of priors well because it effects the cost function of both the legal and illegal side. The sign of the coefficient is determined by which aspect dominates. You would expect τ to act the same way. The shortfall of the model corresponds with workrel, the shortfall may be because in this model and the 1980 model this was determined not to be significant, so this paper need to collect more data to do a more robust analysis, but the reason why it may not be positive is that many work release programs do not increase legal skills. Many work release programs are oriented towards low skill manual labor, thus not having any effect on the model. Supervision was also not significant, however the author of this paper ran an OLS regression on the inmate population which did return to jail against the length of time they returned and found that supervision caused the length of time to

be longer, supervision appears to increase the risk associated with getting caught which increases the cost function of illegal activities but does not increase the payout, but when the supervision ends the utility structure returns to normal. Age is the next aspect, it is negative, but the negative aspect may correspond with increased mortality rates, this may be one of the reasons why you see higher a higher mean prison population today versus thirty years ago, as hospitalization care, especially trauma care goes up, life expectancy has increased across the entire population, but with better trauma care we would expect to see higher life expectancy of incarcerated people. As for school we are using it as a proxy for legal skills (s) this affects both profit functions, but it decreases $g(\bullet)$ which means the cost function of legal profit decreases resulting in decreased recidivism. This corresponds with the negative coefficient we get from the logit regression. This model does not explain why crimes to property or to a person may decrease crime. The married function increases the cost to illegal profits via the $E[f(p,u)|A_{t+1}]$ function, but it does not affect the legal profit cost function which is one reason why we would expect it to have a negative coefficient on recidivism. The last coefficient is white; in order to understand the coefficient associated with race we look at the $g(\bullet)$ function because it is a proxy for discrimination we would expect that g_d to be increasing causing the cost associated with legal profit utility to increase. We would expect to see a substitution to illegal profits as g_d increases. When we ran the 1980s data we achieved similar results.

Table 14 Results from Logit Regression 1980s Cohort

***Rule	***Alchy	***Male	Workrel	***Priors	***Tservd	*Age	***Scho ol	*Perso n	***Marrie d	***Whit e
.98540 7 (.2519)	.436371 (.0647)	.41472 8 (.1387)	.152354 (.0629)	.145214 (.0132)	.012597 (.0015)	- .00434 (.0004)	-.05268 (.0135)	-.12078 (.1012)	-.24991 (.0751)	-.36406 (.2485)

(standard errors in parenthesis) *** indicates that is significant at .001 level, * it is significant .05 level, t it is significant at .1 level

We see similar magnitudes and orderings as in the previous case. In each case we can see that variables that affect just one utility structure, without affecting the other will have larger effects in either the positive or negative direction depending on which cost structure they are affecting. Variables that affect both cost structures tend to have coefficients closer to zero.

Both of these data sets support the Hypothesis. We have evidence that supports this model if Rule and Male were determined to be positive, and white, married, and school were negative because they have the largest one-sided effect on our model. Priors and Tserve are near zero, or not significant because they are influenced by both sides of the model.

Because the costs associated with changing different variables are not uniform it would be helpful to look at the marginal effects of the variables.

Table 15 Marginal Effects from Logit Regression

White	Alchy	Male	Super	Married	Propty	Priors	School	Rule	Age	Tservd
-.11443	.12918	.13989	-.00248	-.03533	-.01251	.03643	-.01051	.33718	-.00097	.00393

Although it would seem difficult to change some of these variables (white, male, married) because we have the theoretical model we may be able to effect the variables without changing them. For example, it would be difficult to change

somebody's race, but it would be less difficult to decrease discrimination through community education and outreach programs, and affirmative action mandates. According to the model this paper presented it would have similar effects. We could affect the male variable via the family function, if prisons facilitated family visits we may see a stronger tie to family which would cause larger effects via the $E[f(p,u)|A_{t+1}]$ function. And if prisons offered marriage counseling it would have an effect on the $E[f(p,u)|A_{t+1}]$ function as well. The most important aspect may be an incentive scheme while in prison which rewards a prisoner who follows to rules.

Supervision

Because there was not a carefully selected control group which determined which criminals from our study were released with supervision in the Schmidt and Witte data set, the results were partially biased. In the Schmidt and White case study the selection was based on the crime and personality of the crime. However to get a better look at how Supervision may affect our model We will look at a Meta-analysis conducted by Douglas Lipton Robert Martinson and Judith Wilks in their book *The Effectiveness of Correctional Treatment A Survey of Treatment Evaluation Studies* (1976) . They performed a meta-analysis of a series of studies with regards to the effect of probation on both young (13-18) and older offenders. After examining 17 studies which totaled about 20,000 subjects they were able to determine that with randomly assigned probation supervision, children with more intense supervision, meaning that the probation officer working with the child had less than 16 case loads, compared to the control in which the probation officer had a

case load of 50-101, were less likely to return to prison. Because of the randomness of the probation selection their study may be less biased. The results were lower recidivism within the time period in which the case worker is working with the individual. Increased supervision would increase the cost of the program, which would cause an increase in our $C_1(SV)$ from the first equation and $(E[c(k,e,p,r)|i,u])$ from the second equation. In fact on average the cost increased by 10 percent per case load. We established that — (equation 3), and that — (equation 4) which would indicate that this will cause a decrease in the amount of crime produced. Lipton et al. concluded that “If the studies are pooled ...all comparisons indicate that younger offenders under intensive supervision performed better than controls. (Lipton, Martinson, & Wilks, 1976)

In the only cost study conducted by the group of surveys examined by Lipton et al, we find that intense supervision for girls had a greater decrease in the cost of crime prevention, Steward Adams (1965) found that in his study of young women in the criminal justice system that the control group cost \$240 a month, which accounted for supervision, detention and placement cost compared to \$185 for the group that was in the intensive supervision group.

Time Served

Similar to the Supervision variable time served may be biased because of the fact that those criminals with longer time served are likely to have participated in more crime in their past, and the crime they committed had a larger impact on the social economical cost the society pays for crime. The type of criminal with longer

time served would be more likely to commit a crime in the future. So in order to get intuition for unbiased results we can look at a case study in San Diego. In 1993 to 2001, San Diego was forced to cut their criminal justice budget, it also decreased misdemeanor arrest by 1%, and prison sentences were reduced by 25%. During this period of time violent crimes in San Diego decreased by 43%. During that same period of time the nationwide average was a reduction by 23%. By looking at that same time period we can see that of the states with the largest increases to prison their prison population (i.e. Idaho, West Virginia, Wisconsin, Texas, Mississippi, North Dakota, Montana, Tennessee, Colorado, and Utah) all of those states had an increase in the percentage of violent crime above the national average. Of the 10 states with the lowest percent increase in prisoners all except two of those states were below the national average. Because nothing changed with the nature of the prisoners in any of these states this gives strong evidence that it the length of time served which cause an increase in the probability of crime increasing. (Jacobson, 2005)

Conclusion

Using the Philip-Votey Model this paper was able to prove that there is an optimal point in which resources should be allocated to minimize the cost of crime. This paper then used the measurement for the cost of the offense function introduced by the Philip-Votey model, the Sellin-Wolfgang measurement. This measurement used the Presidential Commission report to create an upper bound for the price vector. The Sellin-Wolfgang measurement then log linearized the

results of their survey to determine the cost associated with each crime. This paper showed that if we use the assumption that our society is optimizing their resources the upper bound of this Sellin Wolfgang study is no longer correct, and the upper bound would be higher and dynamically increasing each year.

The Phillip-Votey did not elaborate on the social economic causes which cause crime generation. In order to determine what those causes are we looked at the studies produced by Liska, Chamlin, and Reed in their book *Testing the Economic Production and Conflict Models of Crime Control* showed that inequality, and racism . Then this paper looked at Richard Rosenfeld and Steven Messner paper *The Social Sources of Homicide in Different Types of Societies*, which showed that inequality and ineffective legal system, cause increased levels of crime. Then we looked at Ralphael Winter-Ebmer's paper *The Effect of Unemployment on Crime* which showed unemployment increases crime. This paper expanded the data internationally, and uses a fractional logit model to increase efficiency. We use the hypothesis that unemployment, inequality, and a corrupt legal system will cause increased crime. This unemployment and a corrupt legal system was proven to significant at the 99.9%. Inequality was proven to be significant at the 90% level.

We then looked at the sector of society that had the largest effect on the cost of crime control resources the prison system and created a hypothesis for the utility structure faced by a prisoner

The Hypothesized model showed that the largest impact on whether or not a criminal would return to committing crime were the demographics of associated

with Rule and Male white, married, and school because they have the largest one-sided effect on our model. This paper would also expect that priors, T_{served} would be near zero, or not significant because they are influenced by both sides of the model. This is what our model show. This finding supports evidence that if a state worked on shaping a criminal utility function with regards to payoffs of crime, increasing family relations during time incarcerated, decreasing racism, and increasing levels of schooling they should be able to have a lower recidivism rate than by just increasing prison sentences.

Appendix:

Figure 1

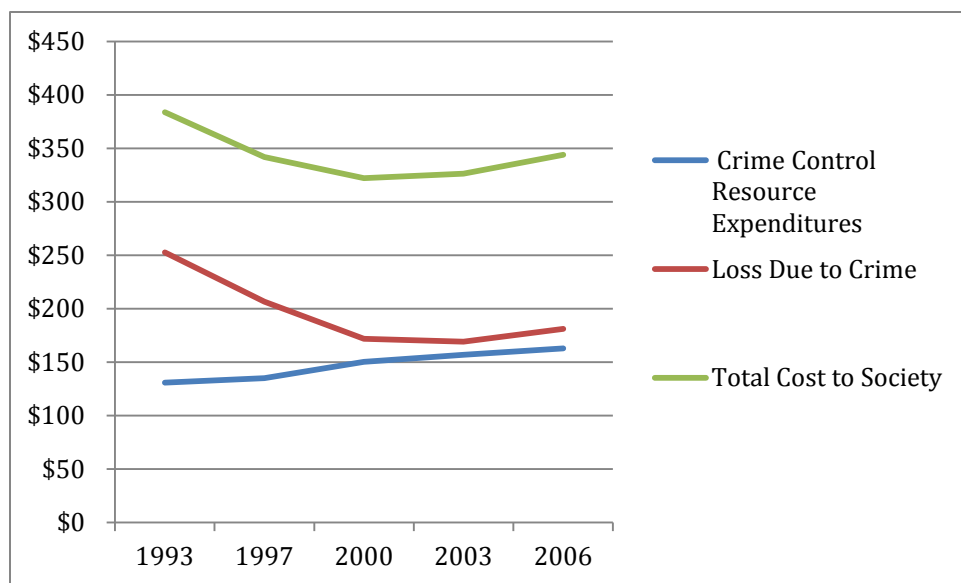
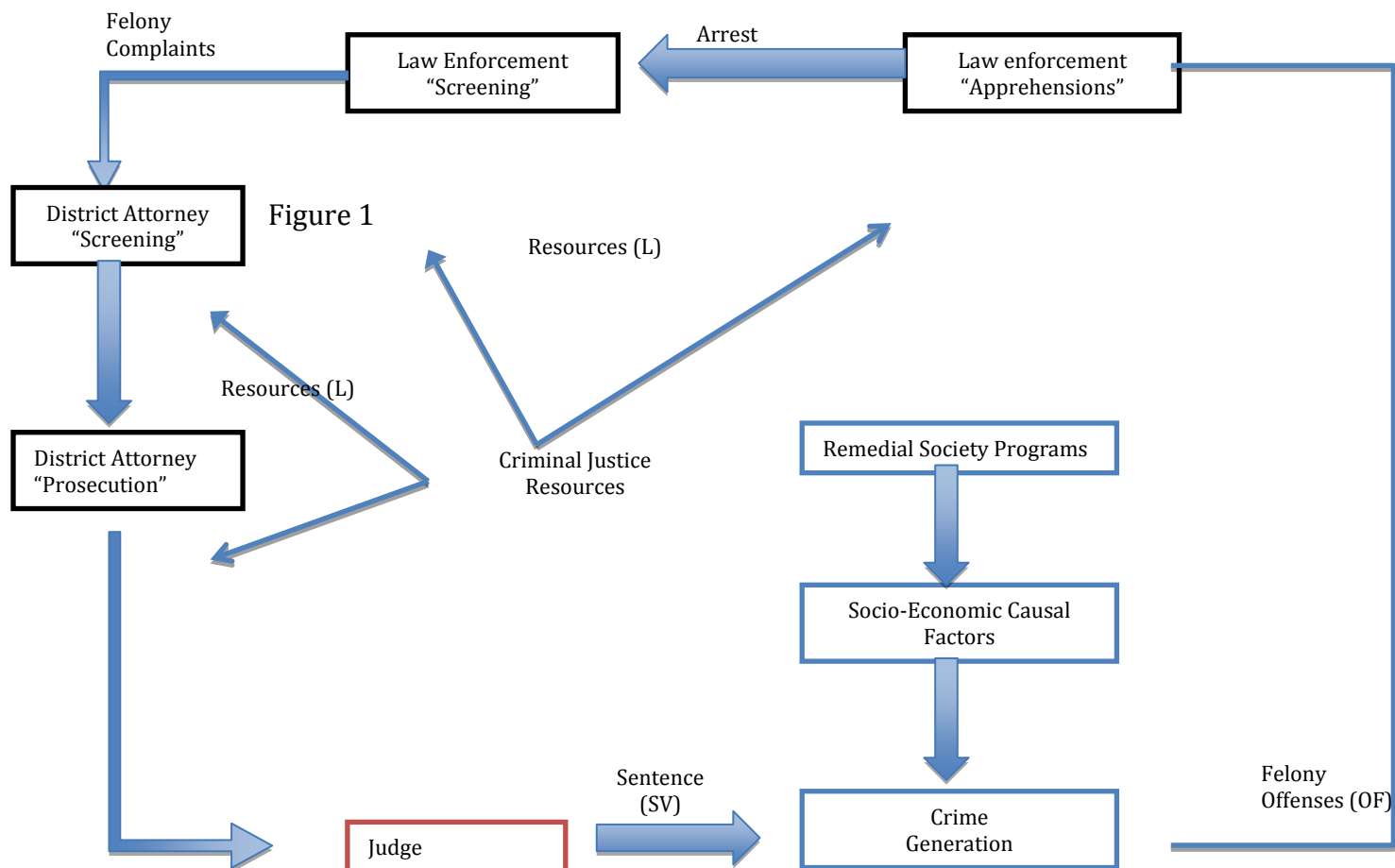


Figure 1 shows the total cost of Society by crime between the years 1993-2006

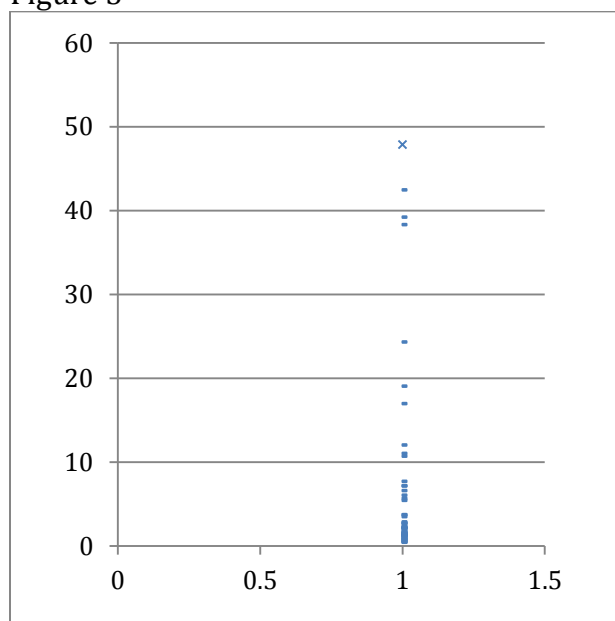
Figure 2

Adaption of Phillips-Votey Figure 2.1 illustration *A Schematic Illustration of Crime Generation and Crime Cost*



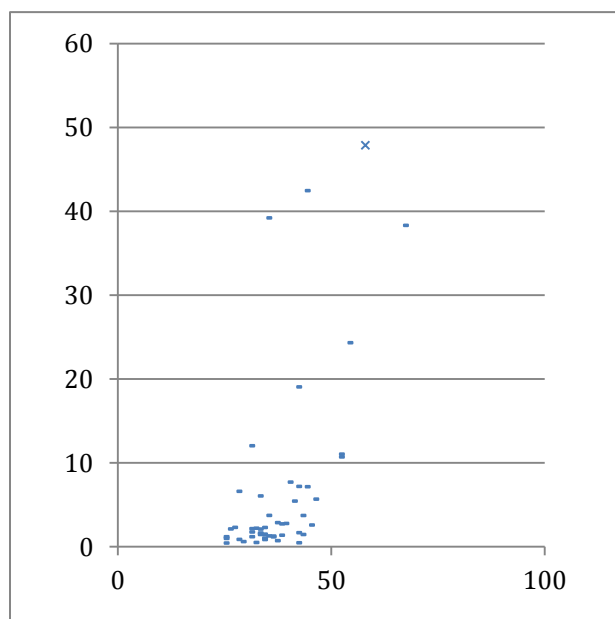
This shows that as the number of offenses increases the conviction ratio will decrease, this means that as more people commit crimes a lower percent of them will be successfully convicted, without changes to the allotment of resources. The second derivative shows that it is decreasing at a decreasing rate. The third function shows that as resources for convictions increase the conviction ratio will increase.

Figure 3



This chart is the average number of murders per 100,000 people for the years we have on record. It shows a thick clustering near the bottom of the chart, and the majority (37 of the 51 countries represented) have a murder rate of less than five people per 100,000 people. All except 9 countries are less than a murder rate of 10 people per 100,000 people. It is those remaining nine, Venezuela, Colombia, Spain, Russia, Mexico, Kazakhstan, Ecuador, Chili, and Brazil which have a significant impact on our model.

Figure 4



This shows how murders increase with a higher gini coefficient.

Table 16 Estimates of Social Loss Rates for 61 Offenses (in 1979 dollars): Derived by Phillips and Votey

Homicide	\$360,729
Rape	\$27,958.30
Selling Heroin	\$11,278.20
Kidnapping-\$1000 Ransom paid	\$11,278.20
Perjury	\$7308.27
Assault-Victim Hospitalized	\$6986.68
Robbery with Weapon	\$5439.73
Arson-Set Fire to Garage	\$5439.73
Incest-Intercourse with Sister	\$3855.55
Robbery without Weapon	\$3249.81
Assault-Victim Treated, Released	\$1580.88
Larceny \$12255	\$1568.32

Embezzled \$1000 from Employer	\$1435.26
Auto Theft	\$1,364.74
Offender Exposes Genitals in public	\$938.68
Burglary	\$926.19
Illegal Possession of Gun	\$917.61
Larceny \$2451	\$724.26
Running a Gambling House	\$412.02
Check Fraud-Singing False Name	\$367.68
Incest-Intercourse with Stepdaughter	\$295.61
Passing Worthless Checks	\$257.37
Larceny between \$100 and \$2500	\$242.63
Larceny \$122.55	\$170.47
Prostitute in House of Prostitution	\$111.24
Possession of Heroin	\$101.64
Larceny \$49.02	\$110.78
Soliciting Act of Prostitution	\$110.54
Pimping	\$85.68
Embezzle \$5.00	\$68.84
Selling Alcohol Illegally	\$62.54
Larceny \$12.25	\$56.98
Dangerous Use of Firearms	\$47.22
Throwing a Rock Through Window	\$42.63
Receiving Stolen Property \$100-\$2500	\$23.83
Madam in House of Prostitution	\$23.03
Participating in Dice Game in Alley	\$21.58
Receiving Stolen Property <\$100	\$18.52
Glue Sniffing	\$18.52
Juvenile Drunk on Street	\$14.17
False Fire Alarm	\$13.28
Prowler-Back Yard of Residence	\$12.50
Trespassing	\$10.32
Offender Takes Bets on Numbers	\$8.84
Customer: in House of Prostitution	\$7.50
Beyond Control of Parents	\$5.00
Parole Violation-Juvenile	\$5.00
Customer in Gambling House	\$3.94
Check Cashed: with Insufficient Funds	\$3.39
Obscene Phone Call	\$3.30
Game Law Violation	\$1.98
Incorrigibility	\$1.82
Loitering	\$1.15
Act of Prostitution	\$.82
Wayward	\$.73
Liquor Law Violation	\$.66

Runaway	\$.57
Disturbing the Peace	\$.45
Truancy	\$.15
Vagrancy	\$.09
Intoxicated in Public	\$.07

Code for recidivism, and marginal effects

R code

```
setwd("C:\\Documents and Settings\\Fire_Hawk\\Desktop\\RRRRR")
dat<-read.table("NC1978right.csv", header = T, sep = ",")
fulldat<-read.table("NC1978right.csv", header = T, sep = ",")
setwd("C:\\Documents and Settings\\Fire_Hawk\\Desktop\\RRRRR")
M<-nrow(fulldat)
N<-ncol(fulldat)
olstest<-array(0,dim=c(M,N-4))
library(AER)
fit.lpm<-coef(summary(lm(recid ~ white + alchy + male + junky + super + married +
workrel + propty + person + priors + school + rule + age + tservd, data=dat)))
fit.pro <-glm(recid ~ white + alchy + male +junky + super + married + workrel +
propty + person + priors + school + rule + age + tservd,
family=binomial(link="probit"), data = dat)
fit.log<- glm(recid ~ white + alchy + male +junky + super + married + workrel +
propty + person + priors + school + rule + age + tservd,
family=binomial(link="logit"), data = dat)
summary(fit.pro)
```

```

summary(fit.log)
logLik(fit.pro)
logLik(fit.log)
results<-cbind(coef(fit.pro), coef(fit.log))
results
## compare against how long before they recidivised
M<-nrow(fulldat)
for(i in 1:M){
  ifelse(fulldat$recid[i]==1,olstest[i,1]<-fulldat$white[i],olstest[i,1]<-NA)
  ifelse(fulldat$recid[i]==1,olstest[i,2]<-fulldat$alchy[i],olstest[i,2]<-NA)
  ifelse(fulldat$recid[i]==1,olstest[i,3]<-fulldat$male[i],olstest[i,3]<-NA)
  ifelse(fulldat$recid[i]==1,olstest[i,4]<-fulldat$junky[i],olstest[i,4]<-NA)
  ifelse(fulldat$recid[i]==1,olstest[i,5]<-fulldat$super[i],olstest[i,5]<-NA)
  ifelse(fulldat$recid[i]==1,olstest[i,6]<-fulldat$married[i],olstest[i,6]<-NA)
  ifelse(fulldat$recid[i]==1,olstest[i,7]<-fulldat$workrel[i],olstest[i,7]<-NA)
  ifelse(fulldat$recid[i]==1,olstest[i,8]<-fulldat$propty[i],olstest[i,8]<-NA)
  ifelse(fulldat$recid[i]==1,olstest[i,9]<-fulldat$person[i],olstest[i,9]<-NA)
  ifelse(fulldat$recid[i]==1,olstest[i,10]<-fulldat$priors[i],olstest[i,10]<-NA)
  ifelse(fulldat$recid[i]==1,olstest[i,11]<-fulldat$school[i],olstest[i,11]<-NA)
  ifelse(fulldat$recid[i]==1,olstest[i,12]<-fulldat$rule[i],olstest[i,12]<-NA)
  ifelse(fulldat$recid[i]==1,olstest[i,13]<-fulldat$age[i],olstest[i,13]<-NA)
  ifelse(fulldat$recid[i]==1,olstest[i,14]<-fulldat$tserve[i],olstest[i,14]<-NA)
  ifelse(fulldat$recid[i]==1,olstest[i,15]<-fulldat$time[i],olstest[i,15]<-NA)
}
ols<-na.omit(olstest)
fit<-
lm(ols[,15]~ols[,1]+ols[,2]+ols[,3]+ols[,4]+ols[,5]+ols[,6]+ols[,7]+ols[,8]+ols[,9]+ols
[,10]+ols[,11]+ols[,12]+ols[,13]+ols[,14])
summary(fit)
###Results
Coefficients:
      Estimate Std. Error t value Pr(>|t|)
(Intercept) 22.591576  3.777694  5.980 2.71e-09 ***
ols[, 1]   -0.223891  0.895319  -0.250 0.802565
ols[, 2]   -4.081673  1.084211  -3.765 0.000172 ***
ols[, 3]   -1.218665  2.475544  -0.492 0.622584
ols[, 4]    0.446185  0.988934   0.451 0.651919
ols[, 5]    0.307782  1.000259   0.308 0.758346
ols[, 6]    2.897378  1.072397   2.702 0.006965 **
ols[, 7]   -0.466555  0.929228  -0.502 0.615670
ols[, 8]   -0.300868  1.111694  -0.271 0.786702
ols[, 9]    2.520027  2.136526   1.179 0.238365
ols[, 10]  -0.708177  0.156360  -4.529 6.33e-06 ***
ols[, 11]   0.141753  0.205830   0.689 0.491114

```

```
ols[, 12] -8.350294  4.343779 -1.922 0.054727 .
ols[, 13]  0.020194  0.005191  3.890 0.000104 ***
ols[, 14] -0.123017  0.019740 -6.232 5.80e-10 ***
```

```
fit.pro <- glm(recid ~ white + alchy + male + super + married + propty + priors +
school + rule + age + tservd, family=binomial(link="probit"), data = dat)
fit.log<- glm(recid ~ white + alchy + male + super + married + propty + priors +
school + rule + age + tservd, family=binomial(link="logit"), data = dat)
summary(fit.pro)
summary(fit.log)
logLik(fit.pro)
logLik(fit.log)
results<-cbind(coef(fit.pro), coef(fit.log))
## calculate marginal effects
# First for the Probit Model
k <- length(coef(fit.pro))
b <- as.matrix(coef(fit.pro))
vars <- c("white", "alchy", "male", "super", "married", "propty", "priors", "school",
"rule", "age", "tservd")
X <- as.matrix(cbind(1, dat[, vars]))
xbar <- apply(X, 2, mean)
z <- dnorm(sum(xbar * b))
pro.me <- rep(0, k-1)
for(i in 1:(k-1)) {
  pro.me[i] <- z * b[i+1]
}
print(round(pro.me, 5))
# Logit Marginal effects:
k<-length(coef(fit.log))
b <- as.matrix(coef(fit.log))
w <- dlogis(sum(xbar * b))
log.me <- rep(0, k-1)
for(i in 1:(k-1)) {
  log.me[i] <- w * b[i+1]
}
print(round(log.me, 5))
##Our probit model is the best fitting
### D - LR Test Statistic
restricted.probit <- glm(recid ~ 1, family=binomial(link="probit"), data=dat)
restricted.logit <- glm(recid ~ 1, family=binomial, data=dat)
LR.pro <- -2*(logLik(restricted.probit) - logLik(fit.pro))
LR.log <- -2*(logLik(restricted.logit) - logLik(fit.log))
LR.pro
```

```

LR.log
## allow our pro model to carry only significant level values
fit.log <- glm(recid ~ white + alchy + male + super + married + propty + priors +
school + rule + age + tservd, family=binomial(link="logit"), data = dat)
a<-table(true=fulldat$recid, pred=round(fitted(fit.pro)))
a
percentage<-(a[1]+a[4])/sum(a)
percentage
## Goodness of fit via McFadden's pseudo-R2
fit.log0<-update(fit.log, formula=~1)
1-as.vector(logLik(fit.log)/logLik(fit.log0))
## compair against 1980 data
setwd("C:\\Documents and Settings\\Fire_Hawk\\Desktop\\RRRRR")
dat<-read.table("NC1980right.csv", header = T, sep = ",")
fulldat<-read.table("NC1980right.csv", header = T, sep = ",")
setwd("C:\\Documents and Settings\\Fire_Hawk\\Desktop\\RRRRR")
M<-nrow(fulldat)
N<-ncol(fulldat)
olstest<-array(0,dim=c(M,N-4))
library(AER)
fit.lpm<-coef(summary(lm(recid ~ white + alchy + male + junky + super + married +
workrel + propty + person + priors + school + rule + age + tservd, data=dat)))
fit.pro <-glm(recid ~ white + alchy + male +junky + super + married + workrel +
propty + person + priors + school + rule + age + tservd,
family=binomial(link="probit"), data = dat)
fit.log<- glm(recid ~ white + alchy + male +junky + super + married + workrel +
propty + person + priors + school + rule + age + tservd,
family=binomial(link="logit"), data = dat)
summary(fit.pro)
summary(fit.log)
summary(fit.pro)
summary(fit.log)
logLik(fit.pro)
logLik(fit.log)
results<-cbind(coef(fit.pro), coef(fit.log))
write.csv(results, "poopstain.csv")
## calculate marginal effects
# First for the Probit Model
k <- length(coef(fit.pro))
b <- as.matrix(coef(fit.pro))
vars <- c("white", "alchy", "male","junky", "super", "married", "workrel", "propty",
"person", "priors", "school", "rule", "age", "tservd")
X <- as.matrix(cbind(1, dat[, vars]))
xbar <- apply(X, 2, mean)

```

```

z <- dnorm(sum(xbar * b))
pro.me <- rep(0, k-1)
for(i in 1:(k-1)) {
  pro.me[i] <- z * b[i+1]
}
print(round(pro.me, 5))
# Logit Marginal effects:
k<-length(coef(fit.log))
b <- as.matrix(coef(fit.log))
w <- dlogis(sum(xbar * b))
log.me <- rep(0, k-1)
for(i in 1:(k-1)) {
  log.me[i] <- w * b[i+1]
}
print(round(log.me, 5))
##C - Prediction tables
b<-table(true=fulldat$recid, pred=round(fitted(fit.pro)))
c<-table(true=fulldat$recid, pred=round(fitted(fit.log)))
b
c
percentageb<-(b[1]+b[4])/sum(b)
percentageb
percentagec<-(c[1]+c[4])/sum(c)
percentagec
recid <- sum(fulldat[,17])
nonrecid <- nrow(fulldat)- recid
recid
nonrecid
##Our probit model is the best fitting

### D - LR Test Statistic
restricted.probit <- glm(recid ~ 1, family=binomial(link="probit"), data=dat)
restricted.logit <- glm(recid ~ 1, family=binomial, data=dat)
LR.pro <- -2*(logLik(restricted.probit) - logLik(fit.pro))
LR.log <- -2*(logLik(restricted.logit) - logLik(fit.log))
LR.pro
LR.log
## allow our pro model to carry only significant level values
fit.log <-glm(recid ~ white + alchy + male + super + married + propty + priors +
school + rule + age + tservd, family=binomial(link="logit"), data = dat)
## prediction table
a<-table(true=fulldat$recid, pred=round(fitted(fit.pro)))
a
percentage<-(a[1]+a[4])/sum(a)

```



```
percentage
## Goodness of fit via McFadden's pseudo-R2
fit.log0<-update(fit.log, formula=~1)
1-as.vector(logLik(fit.log)/logLik(fit.log0))
```

Code for Determining SE portion of paper

```
### r code for gdp and crime
setwd("H:\\")
dat<-read.table("gdpandcrime.csv", header = T, sep = ",")
M<-nrow(dat)
N<-ncol(dat)
olstesttotcrim<-array(0,dim=c(M,2))

## refrence for per capita GDP http://pwt.econ.upenn.edu/php\_site/pwt\_index.php

## crime on per capita real GDP in USA 1960-2011
```

```
fit<-lm(dat$TotalCrime~dat$change)
```

```
summary(fit)
```

```
fit<-lm(dat$fralogtotcrim~dat$change)
summary(fit)
```

```
### as GDP increases so does crime only significant at the 95% level low rsqrd
```

```
#violentcrime<-as.numeric(dat$ViolentCrime)
```

```
fit1<-lm(dat$TotalNOMONEY~dat$change)
fit2<-lm(dat$TotalMONEY~dat$change)
```

```
summary(fit1)
summary(fit2)
```

```
fit1<-lm(dat$fralogtotnomon~dat$change)
fit2<-lm(dat$fralogtotmon~dat$change)
```

```
summary(fit1)
```

```

summary(fit2)

fit1<-lm(dat$fralogtotnomon~dat$changechange)
fit2<-lm(dat$fralogtotcrim~dat$changechange)

summary(fit1)
summary(fit2)

##find what increases with dat$change

fit3<-lm(dat$fraclograp~dat$change)

fit4<-lm(dat$fraclogrob~dat$change)

fit5<-lm(dat$fraclogass~dat$change)

fit6<-lm(dat$fraclogpro~dat$change)

fit7<-lm(dat$fraclogbur~dat$change)

fit8<-lm(dat$fraclogthe~dat$change)

fit9<-lm(dat$VEHPER1000~dat$change)

fit10<-lm(dat$murper1000~dat$change)

summary(fit3)
summary(fit4)
summary(fit5)
summary(fit6)
summary(fit7)
summary(fit8)
summary(fit9)
summary(fit10)

dat0<-read.table("India.csv", header = T, sep = ",")
fitcrime<-lm(dat0$totalcrimperperson~dat0$changeingdp)
summary(fitcrime)
fitfraclog<-lm(dat0$fractcpp~dat0$changeingdp)
summary(fitfraclog)

fitmur<-lm(dat0$fracmur~dat0$changeingdp)

```

```

fitbur<-lm(dat0$fraclogbur~dat0$changeingdp)

summary(fitmur)
summary(fitbur)

#http://ncrb.nic.in/CII-2009-NEW/cii-2009/Table%204.1.pdf
#http://ncrb.nic.in/
#http://ncrb.nic.in/CII-2009-NEW/cii-2009/Table%20Contents.htm

dat01<-read.table("gini2.csv",header = T, sep = ",")
fitmur<-lm(dat01$savemurd~dat01$Gini)
summary(fitmur)
fitmur1<-lm(dat01$fracmur~dat01$Gini)
summary(fitmur1)

dat02<-read.table("gini3.csv", header = T, sep = ",")
fitmur<-lm(dat02$fracmur~dat02$Gini + dat02$law)


dat1<-read.table("reui.csv", header = T, sep = ",")

names(dat1)

fiteiu<-lm(dat1$Murder~ dat1$GDP.realchange)
summary(fiteiu)
fiteiu1<-lm(dat1$Murder~dat1$firstworld + dat1$GDP.realchange)
summary(fiteiu1)

##check geography
fiteiu2<-lm(dat1$Murder~dat1$Asia + dat1$North.America + dat1$South.America +
dat1$Europe +dat1$Africa + dat1$Oceania + dat1$GDP.realchange)

unemploymentpercent<-as.numeric(dat1$Recordedunemployment.)

fiteiu3<-lm(dat1$Murder~unemploymentpercent)

summary(fiteiu3)

fiteiu3.0<-lm(dat1$fracmurd~unemploymentpercent)
summary(fiteiu3.0)

dat4<-read.table("reui3.csv", header= T, sep = ",")

```

```
fit1<-
lm(dat4$fracmurd~dat4$Recordedunemployment.+dat4$Inequality+dat4$Legal.re
gulatoryrisk.100.high)
```

```
fiteiu3.1<-lm(dat1$Murder~dat1$Asia + dat1$North.America + dat1$South.America
+ dat1$Europe +dat1$Africa + dat1$Oceania + dat1$Male.ofpopulation)
summary(fiteiu3.1)
```

```
fiteiu4<-lm(dat1$Murder~dat1$Asia + dat1$North.America + dat1$South.America +
dat1$Europe +dat1$Africa + dat1$Oceania + dat1$ofpopulationaged15.64)
summary(fiteiu4)
```

```
fiteiu5<-lm(dat1$Murder~dat1$Asia + dat1$North.America + dat1$South.America +
dat1$Europe +dat1$Africa + dat1$Oceania + dat1$ofpopulationaged15.19)
summary(fiteiu5)
```

```
fiteiu6<-lm(dat1$Murder~dat1$Asia + dat1$North.America + dat1$South.America +
dat1$Europe +dat1$Africa + dat1$Oceania + dat1$ofpopulationaged20.24)
summary(fiteiu6)
```

```
fiteiu7<-lm(dat1$Murder~dat1$Asia + dat1$North.America + dat1$South.America +
dat1$Europe +dat1$Africa + dat1$Oceania + dat1$ofpopulationaged0.4)
summary(fiteiu7)
```

```
fiteiu8<-lm(dat1$Murder~dat1$Asia + dat1$North.America + dat1$South.America +
dat1$Europe +dat1$Africa + dat1$Oceania + dat1$ofpopulationaged5.9)
summary(fiteiu8)
```

```
fiteiu9<-lm(dat1$Murder~dat1$Asia + dat1$North.America + dat1$South.America +
dat1$Europe +dat1$Africa + dat1$Oceania + dat1$ofpopulationaged10.14)
summary(fiteiu9)
```

```
fiteiu10<-lm(dat1$Murder~dat1$Asia + dat1$North.America + dat1$South.America
+ dat1$Europe +dat1$Africa + dat1$Oceania + dat1$ofpopulationaged25.29)
```

```
summary(fiteiu10)
```

```
fiteiu11<-lm(dat1$Murder~dat1$Asia + dat1$North.America + dat1$South.America
+ dat1$Europe +dat1$Africa + dat1$Oceania + dat1$ofpopulationaged30.34)
summary(fiteiu11)
```

```
fiteiu12<-lm(dat1$Murder~dat1$Asia + dat1$North.America + dat1$South.America
+ dat1$Europe +dat1$Africa + dat1$Oceania + dat1$ofpopulationaged35.39)
summary(fiteiu12)
```

```
fiteiu13<-lm(dat1$Murder~dat1$Asia + dat1$North.America + dat1$South.America
+ dat1$Europe +dat1$Africa + dat1$Oceania + dat1$ofpopulationaged40.44)
summary(fiteiu13)
```

```
fiteiu13<-lm(dat1$Murder~dat1$Asia + dat1$North.America + dat1$South.America
+ dat1$Europe +dat1$Africa + dat1$Oceania + dat1$ofpopulationaged45.49)
summary(fiteiu13)
```

```
fiteiu14<-lm(dat1$Murder~dat1$Asia + dat1$North.America + dat1$South.America
+ dat1$Europe +dat1$Africa + dat1$Oceania + dat1$ofpopulationaged50.54)
summary(fiteiu14)
```

```
fiteiu15<-lm(dat1$Murder~dat1$Asia + dat1$North.America + dat1$South.America
+ dat1$Europe +dat1$Africa + dat1$Oceania + dat1$ofpopulationaged55.59)
summary(fiteiu15)
```

```
fiteiu16<-lm(dat1$Murder~dat1$Asia + dat1$North.America + dat1$South.America
+ dat1$Europe +dat1$Africa + dat1$Oceania + dat1$ofpopulationaged60.64)
summary(fiteiu16)
```

```
fiteiu17<-lm(dat1$Murder~dat1$Asia + dat1$North.America + dat1$South.America
+ dat1$Europe +dat1$Africa + dat1$Oceania + dat1$ofpopulationaged65.69)
summary(fiteiu17)
```

```
fiteiu18<-lm(dat1$Murder~dat1$Asia + dat1$North.America + dat1$South.America
+ dat1$Europe +dat1$Africa + dat1$Oceania + dat1$ofpopulationaged70.74)
summary(fiteiu18)
```

```
fiteiu19<-lm(dat1$Murder~dat1$Asia + dat1$North.America + dat1$South.America
+ dat1$Europe +dat1$Africa + dat1$Oceania + dat1$ofpopulationaged75.79)
summary(fiteiu19)
```

```
fiteiu20<-lm(dat1$Murder~dat1$Asia + dat1$North.America + dat1$South.America
+ dat1$Europe +dat1$Africa + dat1$Oceania + dat1$ofpopulationaged80.84)
```

```
summary(fiteiu20)
```

```
carsper1000<-as.numeric(dat1$Passengercars.stockper1.000pop.)
```

```
fiteiu21<-lm(dat1$Murder~dat1$Asia + dat1$North.America + dat1$South.America  
+ dat1$Europe +dat1$Africa + dat1$Oceania + carsper1000)  
summary(fiteiu21)
```

```
petrol<-as.numeric(dat1$Petrolconsumption.tonnes.)
```

```
fiteiu22<-lm(dat1$Murder~dat1$Asia + dat1$North.America + dat1$South.America  
+ dat1$Europe +dat1$Africa + dat1$Oceania + petrol)  
summary(fiteiu22)
```

```
fiteiu23<-lm(dat1$Murder~dat1$Asia + dat1$North.America + dat1$South.America  
+ dat1$Europe +dat1$Africa + dat1$Oceania +  
dat1$Workingagepopulationgrowth..pa.)  
summary(fiteiu23)
```

```
Employmentgrowth<-as.numeric(dat1$Employmentgrowth..pa.)
```

```
fiteiu24<-lm(dat1$Murder~dat1$Asia + dat1$North.America + dat1$South.America  
+ dat1$Europe +dat1$Africa + dat1$Oceania + Employmentgrowth + petrol)  
summary(fiteiu24)
```

```
fiteiu25<-lm(dat1$Murder~dat1$Asia + dat1$North.America + dat1$South.America  
+ dat1$Europe +dat1$Africa + dat1$Oceania + dat1$Productivityofcapital.ICOR.)  
summary(fiteiu25)
```

```
fiteiu26<-lm(dat1$Murder~dat1$Asia + dat1$North.America + dat1$South.America  
+ dat1$Europe +dat1$Africa + dat1$Oceania + dat1$ofpopulationaged20.24 +  
dat1$ofpopulationaged15.19 + dat1$Female.ofpopulation)  
summary(fiteiu26)
```

```
fiteiu27<-lm(dat1$Murder~dat1$South.America + dat1$ofpopulationaged20.24 +  
dat1$ofpopulationaged15.19 + dat1$Female.ofpopulation)  
summary(fiteiu27)
```

```
fiteiu28<-lm(dat1$Murder~dat1$South.America + dat1$ofpopulationaged20.24 +  
dat1$Female.ofpopulation + petrol)  
summary(fiteiu28)
```

###Look at political and economic stability

```
dat2<-read.table("reui2.csv", header = T, sep = ",")
```

```
fiteiu29<-lm(dat2$Murder~dat2$South.America + dat2$ofpopulationaged20.24 +
dat2$Female.ofpopulation + petrol + dat2$Riskofsocialunrest.5.low.+
dat2$Impactofcrime.5.low.+ dat2$Degreeofpropertyrightsprotection.5.high. +
dat2$Settingupnewbusinesses.5.lowregulation. + dat2$Freedomtocompetete.5.high.+
dat2$Promotionofcompetition.5.high. + dat2$Intellectualpropertyprotection.5.high.
+ dat2$Pricecontrols.5.few. + dat2$Lobbyingbyspecialinterestgroups.5.low. +
dat2$Stateownership.control.5.low. )
summary(fiteiu29)
```

```
dat3<-read.table("reui2.csv", header = T, sep = ",")
```

```
M<-na.omit(dat3)
```

```
petrol<-as.numeric(M$Petrolconsumption.tonnes.)
```

```
fiteiu30<-lm(M$Murder~M$South.America + M$ofpopulationaged20.24 +
M$Female.ofpopulation + petrol + M$Riskofsocialunrest.5.low.+
M$Impactofcrime.5.low.+ M$Degreeofpropertyrightsprotection.5.high. +
M$Settingupnewbusinesses.5.lowregulation. + M$Freedomtocompetete.5.high.+
M$Promotionofcompetition.5.high. + M$Intellectualpropertyprotection.5.high. +
M$Pricecontrols.5.few. + M$Lobbyingbyspecialinterestgroups.5.low. +
M$Stateownership.control.5.low.)
```

```
fiteiu31<-lm(M$Murder~M$South.America + M$ofpopulationaged20.24 + petrol)
```

```
summary(fiteiu30)
```

```
fiteiu31<-lm(M$Murder~M$South.America + M$ofpopulationaged20.24 +
M$Female.ofpopulation + petrol + M$Riskofsocialunrest.5.low.+
M$Impactofcrime.5.low.+ M$Degreeofpropertyrightsprotection.5.high. +
M$Settingupnewbusinesses.5.lowregulation. + M$Freedomtocompetete.5.high.+
M$Promotionofcompetition.5.high. + M$Intellectualpropertyprotection.5.high. +
M$Pricecontrols.5.few. + M$Lobbyingbyspecialinterestgroups.5.low. +
M$Stateownership.control.5.low.)
```

```
summary(fiteiu31)
```

```
fiteiu32<-lm(M$Murder~M$South.America + M$X.ofHHsearning.US.10.000p.a.+
M$X.ofHHsearning.US.15.000p.a.+ M$Averagewages.monthly.+
M$Medianhouseholdincome.US.. + M$X.ofHHsearning.US.5.000p.a. +
M$X.ofHHsearning.US.3.000p.a.+ M$X.ofHHsearning.US.1.000p.a. +
M$.ofHHsearning.US$1,000p.a.+ M$ofpopulationaged20.24 +
M$Female.ofpopulation + petrol + M$Riskofsocialunrest.5.low.+
M$Impactofcrime.5.low.+ M$Degreeofpropertyrightsprotection.5.high. +
M$Settingupnewbusinesses.5.lowregulation. + M$Freedomtocompete.5.high.+
M$Promotionofcompetition.5.high. + M$Intellectualpropertyprotection.5.high. +
M$Pricecontrols.5.few. + M$Lobbyingbyspecialinterestgroups.5.low. +
M$Stateownership.control.5.low.)
summary(fiteiu32)
```

```
newdat1<-na.omit(dat1)
```

```
petrol<-as.numeric(m$Petrolconsumption.tonnes.)
```

```
fitM1<-lm(M$Murder~M$South.America + M$ofpopulationaged20.24 +
M$Female.ofpopulation + petrol + M$Inequality)
summary(fitM1)
```

```
## determine the inequality =((((100-DB2)-(100-DC2))*1)+(((100-DB2)-(100-
DD2))*2)+(((100-DB2)-(100-DE2))*3)+(((100-DB2)-(100-DF2))*4)+(((100-DB2)-
(100-DG2))*5)+(((100-DB2)-(100-DH2))*6)+(((100-DB2)-(100-DI2))*7)+(((100-
DB2)-(100-DJ2))*8)+(((100-DC2)-(100-DD2))*1)+((DC2-DE2)*2)+((DC2-
DF2)*3)+((DC2-DG2)*4)+((DC2-DH2)*5)+((DC2-DI2)*5)+((DC2-DJ2)*6)+((DD2-
DE2)*1)+((DD2-DF2)*2)+((DD2-DG2)*3)+((DD2-DH2)*4)+((DD2-DI2)*5)+((DD2-
DJ2)*6)+((DE2-DF2)*1)+((DE2-DG2)*2)+((DE2-DH2)*3)+((DE2-DI2)*4)+((DE2-
DJ2)*5)+((DF2-DG2)*1)+((DF2-DH2)*2)+((DF2-DI2)*3)+((DF2-DJ2)*4)+((DG2-
DH2)*1)+((DG2-DI2)*2)+((DG2-DJ2)*3)+((DH2-DI2)*1)+((DH2-DJ2)*2)+((DI2-
DJ2)*1)
```

Table results for the code

Call:

```
lm(formula = dat1$Murder ~ dat1$Asia + dat1$North.America +
dat1$South.America +
  dat1$Europe + dat1$Africa + dat1$Oceania + dat1$Male.ofpopulation)
```

Residuals:

```
Min    1Q  Median    3Q   Max
```


-20.252 -3.535 -2.322 0.580 39.447

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-25.9787	25.1076	-1.035	0.3017
dat1\$Asia	1.7489	9.6172	0.182	0.8558
dat1\$North.America	3.7669	9.8133	0.384	0.7014
dat1\$South.America	20.5515	9.6711	2.125	0.0345 *
dat1\$Europe	2.0332	9.5948	0.212	0.8323
dat1\$Africa	6.4962	9.7460	0.667	0.5056
dat1\$Oceania	0.1179	9.8024	0.012	0.9904
dat1\$Male.of.population	0.5767	0.4591	1.256	0.2101

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 9.526 on 282 degrees of freedom
 Multiple R-squared: 0.3053, Adjusted R-squared: 0.2881
 F-statistic: 17.71 on 7 and 282 DF, p-value: < 2.2e-16

Call:

```
lm(formula = dat1$Murder ~ dat1$Asia + dat1$North.America +
  dat1$South.America +
  dat1$Europe + dat1$Africa + dat1$Oceania + dat1$ofpopulationaged15.64)
```

Residuals:

Min	1Q	Median	3Q	Max
-19.579	-3.211	-2.482	0.941	39.461

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-5.58560	14.96388	-0.373	0.7092
dat1\$Asia	0.82984	9.64803	0.086	0.9315
dat1\$North.America	2.49888	9.81622	0.255	0.7992
dat1\$South.America	19.93390	9.67865	2.060	0.0404 *
dat1\$Europe	0.44592	9.60462	0.046	0.9630
dat1\$Africa	7.19340	9.76401	0.737	0.4619
dat1\$Oceania	0.05579	9.82093	0.006	0.9955
dat1\$ofpopulationaged15.64	0.13792	0.18094	0.762	0.4466

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 9.543 on 282 degrees of freedom
 Multiple R-squared: 0.3029, Adjusted R-squared: 0.2856

F-statistic: 17.5 on 7 and 282 DF, p-value: < 2.2e-16

Call:

```
lm(formula = dat1$Murder ~ dat1$Asia + dat1$North.America +
    dat1$South.America +
    dat1$Europe + dat1$Africa + dat1$Oceania + dat1$ofpopulationaged15.19)
```

Residuals:

Min	1Q	Median	3Q	Max
-20.309	-3.118	-1.891	0.087	40.456

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-5.9721	10.2491	-0.583	0.5606
dat1\$Asia	2.5628	9.5615	0.268	0.7889
dat1\$North.America	4.6784	9.7525	0.480	0.6318
dat1\$South.America	20.6090	9.5999	2.147	0.0327 *
dat1\$Europe	4.0281	9.5840	0.420	0.6746
dat1\$Africa	6.0844	9.6814	0.628	0.5302
dat1\$Oceania	1.7410	9.7594	0.178	0.8585
dat1\$ofpopulationaged15.19	0.9265	0.3978	2.329	0.0206 *

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 9.462 on 282 degrees of freedom

Multiple R-squared: 0.3146, Adjusted R-squared: 0.2976

F-statistic: 18.49 on 7 and 282 DF, p-value: < 2.2e-16

Call:

```
lm(formula = dat1$Murder ~ dat1$Asia + dat1$North.America +
    dat1$South.America +
    dat1$Europe + dat1$Africa + dat1$Oceania + dat1$ofpopulationaged20.24)
```

Residuals:

Min	1Q	Median	3Q	Max
-20.087	-3.061	-1.731	0.189	39.198

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-9.7923	10.3624	-0.945	0.34548
dat1\$Asia	2.0370	9.4919	0.215	0.83023
dat1\$North.America	4.7158	9.6826	0.487	0.62661
dat1\$South.America	20.1947	9.5387	2.117	0.03512 *

```

dat1$Europe      3.9301  9.4891  0.414 0.67907
dat1$Africa      5.3058  9.6316  0.551 0.58216
dat1$Oceania     1.6679  9.6905  0.172 0.86347
dat1$ofpopulationaged20.24 1.4598  0.4888 2.987 0.00307 **

```

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 9.405 on 282 degrees of freedom

Multiple R-squared: 0.3228, Adjusted R-squared: 0.306

F-statistic: 19.21 on 7 and 282 DF, p-value: < 2.2e-16

Call:

```

lm(formula = dat1$Murder ~ dat1$Asia + dat1$North.America +
  dat1$South.America +
  dat1$Europe + dat1$Africa + dat1$Oceania + dat1$ofpopulationaged0.4)

```

Residuals:

```

   Min     1Q   Median     3Q    Max
-19.834 -3.149 -2.344 -0.261 39.633

```

Coefficients:

```

              Estimate Std. Error t value Pr(>|t|)
(Intercept)    0.4734    9.9697  0.047 0.9622
dat1$Asia      1.8968    9.6430  0.197 0.8442
dat1$North.America  3.5635    9.8272  0.363 0.7172
dat1$South.America 20.0792    9.6734  2.076 0.0388 *
dat1$Europe     2.2577    9.6641  0.234 0.8154
dat1$Africa     6.4385    9.7655  0.659 0.5102
dat1$Oceania    0.5015    9.8202  0.051 0.9593
dat1$ofpopulationaged0.4 0.2727    0.2903  0.939 0.3484

```

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 9.538 on 282 degrees of freedom

Multiple R-squared: 0.3036, Adjusted R-squared: 0.2863

F-statistic: 17.56 on 7 and 282 DF, p-value: < 2.2e-16

Call:

```

lm(formula = dat1$Murder ~ dat1$Asia + dat1$North.America +
  dat1$South.America +
  dat1$Europe + dat1$Africa + dat1$Oceania + dat1$ofpopulationaged5.9)

```

Residuals:

Min	1Q	Median	3Q	Max
-19.994	-3.163	-2.368	0.116	39.771

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	0.2836	10.3050	0.028	0.9781
dat1\$Asia	2.0796	9.6829	0.215	0.8301
dat1\$North.America	3.7623	9.8771	0.381	0.7036
dat1\$South.America	20.2675	9.6850	2.093	0.0373 *
dat1\$Europe	2.4031	9.7569	0.246	0.8056
dat1\$Africa	6.9280	9.7577	0.710	0.4783
dat1\$Oceania	0.8511	9.8602	0.086	0.9313
dat1\$ofpopulationaged5.9	0.2700	0.3600	0.750	0.4539

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 9.543 on 282 degrees of freedom

Multiple R-squared: 0.3028, Adjusted R-squared: 0.2855

F-statistic: 17.5 on 7 and 282 DF, p-value: < 2.2e-16

>

>

```
> fiteiu9<-lm(dat1$Murder~dat1$Asia + dat1$North.America + dat1$South.America
+ dat1$Europe +dat1$Africa + dat1$Oceania + dat1$ofpopulationaged10.14)
> summary(fiteiu9)
```

Call:

```
lm(formula = dat1$Murder ~ dat1$Asia + dat1$North.America +
dat1$South.America +
  dat1$Europe + dat1$Africa + dat1$Oceania + dat1$ofpopulationaged10.14)
```

Residuals:

Min	1Q	Median	3Q	Max
-20.135	-3.149	-2.359	-0.070	39.958

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-0.7974	10.3154	-0.077	0.9384
dat1\$Asia	2.1684	9.6573	0.225	0.8225
dat1\$North.America	3.9421	9.8536	0.400	0.6894
dat1\$South.America	20.3984	9.6784	2.108	0.0359 *
dat1\$Europe	2.7255	9.7179	0.280	0.7793
dat1\$Africa	6.8896	9.7496	0.707	0.4804

```
dat1$Oceania      1.0946  9.8527  0.111  0.9116
dat1$ofpopulationaged10.14  0.3701  0.3644  1.016  0.3106
```

```
---
```

```
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Residual standard error: 9.535 on 282 degrees of freedom
Multiple R-squared: 0.304,    Adjusted R-squared: 0.2867
F-statistic: 17.59 on 7 and 282 DF, p-value: < 2.2e-16
```

```
>
```

```
> fiteiu10<-lm(dat1$Murder~dat1$Asia + dat1$North.America +
dat1$South.America + dat1$Europe +dat1$Africa + dat1$Oceania +
dat1$ofpopulationaged25.29)
> summary(fiteiu10)
```

```
Call:
```

```
lm(formula = dat1$Murder ~ dat1$Asia + dat1$North.America +
dat1$South.America +
  dat1$Europe + dat1$Africa + dat1$Oceania + dat1$ofpopulationaged25.29)
```

```
Residuals:
```

```
   Min     1Q  Median     3Q    Max
-20.096 -3.729 -1.661  0.532 38.511
```

```
Coefficients:
```

```
              Estimate Std. Error t value Pr(>|t|)
(Intercept)   -10.3568   10.8010  -0.959  0.3384
dat1$Asia       1.7740    9.5272   0.186  0.8524
dat1$North.America  4.6599    9.7250   0.479  0.6322
dat1$South.America 20.1735    9.5757   2.107  0.0360 *
dat1$Europe     2.8746    9.5026   0.303  0.7625
dat1$Africa     6.4634    9.6553   0.669  0.5038
dat1$Oceania    1.7963    9.7353   0.185  0.8537
dat1$ofpopulationaged25.29 1.6139    0.6245   2.584  0.0103 *
```

```
---
```

```
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Residual standard error: 9.442 on 282 degrees of freedom
Multiple R-squared: 0.3176,    Adjusted R-squared: 0.3007
F-statistic: 18.75 on 7 and 282 DF, p-value: < 2.2e-16
```

```
>
```

```
> fiteiu11<-lm(dat1$Murder~dat1$Asia + dat1$North.America +
dat1$South.America + dat1$Europe +dat1$Africa + dat1$Oceania +
dat1$ofpopulationaged30.34)
> summary(fiteiu11)
```

Call:

```
lm(formula = dat1$Murder ~ dat1$Asia + dat1$North.America +
dat1$South.America +
  dat1$Europe + dat1$Africa + dat1$Oceania + dat1$ofpopulationaged30.34)
```

Residuals:

```
   Min     1Q   Median     3Q      Max
-20.173 -3.642 -2.315  0.635  38.060
```

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-8.3072	11.2456	-0.739	0.4607
dat1\$Asia	1.2473	9.5760	0.130	0.8965
dat1\$North.America	4.0158	9.7703	0.411	0.6814
dat1\$South.America	20.4731	9.6294	2.126	0.0344 *
dat1\$Europe	1.7119	9.5324	0.180	0.8576
dat1\$Africa	7.7988	9.7159	0.803	0.4228
dat1\$Oceania	1.1334	9.7795	0.116	0.9078
dat1\$ofpopulationaged30.34	1.4566	0.7634	1.908	0.0574 .

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 9.492 on 282 degrees of freedom
Multiple R-squared: 0.3103, Adjusted R-squared: 0.2932
F-statistic: 18.13 on 7 and 282 DF, p-value: < 2.2e-16

```
>
> fiteiu12<-lm(dat1$Murder~dat1$Asia + dat1$North.America +
dat1$South.America + dat1$Europe +dat1$Africa + dat1$Oceania +
dat1$ofpopulationaged35.39)
> summary(fiteiu12)
```

Call:

```
lm(formula = dat1$Murder ~ dat1$Asia + dat1$North.America +
dat1$South.America +
  dat1$Europe + dat1$Africa + dat1$Oceania + dat1$ofpopulationaged35.39)
```

Residuals:

```
   Min     1Q   Median     3Q      Max
```

-19.722 -3.411 -2.333 1.223 39.306

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	1.4838	10.6580	0.139	0.8894
dat1\$Asia	1.1889	9.6409	0.123	0.9019
dat1\$North.America	2.8707	9.8122	0.293	0.7701
dat1\$South.America	20.0222	9.6861	2.067	0.0396 *
dat1\$Europe	0.9281	9.5866	0.097	0.9229
dat1\$Africa	7.1269	9.7820	0.729	0.4669
dat1\$Oceania	0.1923	9.8274	0.020	0.9844
dat1\$ofpopulationaged35.39	0.2417	0.6663	0.363	0.7171

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 9.55 on 282 degrees of freedom

Multiple R-squared: 0.3018, Adjusted R-squared: 0.2844

F-statistic: 17.41 on 7 and 282 DF, p-value: < 2.2e-16

>

```
> fiteiu13<-lm(dat1$Murder~dat1$Asia + dat1$North.America +
dat1$South.America + dat1$Europe +dat1$Africa + dat1$Oceania +
dat1$ofpopulationaged40.44)
> summary(fiteiu13)
```

Call:

```
lm(formula = dat1$Murder ~ dat1$Asia + dat1$North.America +
dat1$South.America +
dat1$Europe + dat1$Africa + dat1$Oceania + dat1$ofpopulationaged40.44)
```

Residuals:

Min	1Q	Median	3Q	Max
-19.576	-3.536	-2.361	1.159	39.421

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	0.69077	10.20555	0.068	0.9461
dat1\$Asia	0.96024	9.64232	0.100	0.9207
dat1\$North.America	2.44172	9.82515	0.249	0.8039
dat1\$South.America	19.91613	9.68072	2.057	0.0406 *
dat1\$Europe	0.55247	9.60038	0.058	0.9542
dat1\$Africa	7.27139	9.77228	0.744	0.4574
dat1\$Oceania	-0.02238	9.82566	-0.002	0.9982
dat1\$ofpopulationaged40.44	0.40471	0.58277	0.694	0.4880

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 9.545 on 282 degrees of freedom

Multiple R-squared: 0.3026, Adjusted R-squared: 0.2853

F-statistic: 17.48 on 7 and 282 DF, p-value: < 2.2e-16

Call:

```
lm(formula = dat1$Murder ~ dat1$Asia + dat1$North.America +
  dat1$South.America +
  dat1$Europe + dat1$Africa + dat1$Oceania + dat1$ofpopulationaged45.49)
```

Residuals:

Min	1Q	Median	3Q	Max
-19.644	-3.246	-2.369	1.251	39.544

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	2.69342	10.01129	0.269	0.7881
dat1\$Asia	1.18351	9.66483	0.122	0.9026
dat1\$North.America	2.68567	9.87220	0.272	0.7858
dat1\$South.America	19.95404	9.69201	2.059	0.0404 *
dat1\$Europe	0.80736	9.65653	0.084	0.9334
dat1\$Africa	6.97778	9.77325	0.714	0.4758
dat1\$Oceania	0.07309	9.85037	0.007	0.9941
dat1\$ofpopulationaged45.49	0.09933	0.58763	0.169	0.8659

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 9.552 on 282 degrees of freedom

Multiple R-squared: 0.3015, Adjusted R-squared: 0.2842

F-statistic: 17.39 on 7 and 282 DF, p-value: < 2.2e-16

>

```
> fiteiu14<-lm(dat1$Murder~dat1$Asia + dat1$North.America +
  dat1$South.America + dat1$Europe +dat1$Africa + dat1$Oceania +
  dat1$ofpopulationaged50.54)
> summary(fiteiu14)
```

Call:

```
lm(formula = dat1$Murder ~ dat1$Asia + dat1$North.America +
  dat1$South.America +
  dat1$Europe + dat1$Africa + dat1$Oceania + dat1$ofpopulationaged50.54)
```


Residuals:

Min	1Q	Median	3Q	Max
-20.359	-3.305	-1.992	0.121	38.820

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	7.3495	9.7879	0.751	0.4534
dat1\$Asia	2.4874	9.6083	0.259	0.7959
dat1\$North.America	4.6615	9.8138	0.475	0.6352
dat1\$South.America	20.4630	9.6388	2.123	0.0346 *
dat1\$Europe	3.4588	9.6353	0.359	0.7199
dat1\$Africa	6.4062	9.7184	0.659	0.5103
dat1\$Oceania	1.4086	9.8007	0.144	0.8858
dat1\$ofpopulationaged50.54	-0.9880	0.5606	-1.762	0.0791 .

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 9.501 on 282 degrees of freedom

Multiple R-squared: 0.309, Adjusted R-squared: 0.2919

F-statistic: 18.02 on 7 and 282 DF, p-value: < 2.2e-16

>

```
> fiteiu15<-lm(dat1$Murder~dat1$Asia + dat1$North.America +
dat1$South.America + dat1$Europe +dat1$Africa + dat1$Oceania +
dat1$ofpopulationaged55.59)
> summary(fiteiu15)
```

Call:

```
lm(formula = dat1$Murder ~ dat1$Asia + dat1$North.America +
dat1$South.America +
dat1$Europe + dat1$Africa + dat1$Oceania + dat1$ofpopulationaged55.59)
```

Residuals:

Min	1Q	Median	3Q	Max
-20.529	-3.222	-1.914	0.724	38.974

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	8.0861	9.5157	0.850	0.39618
dat1\$Asia	2.8829	9.4853	0.304	0.76140
dat1\$North.America	5.5482	9.6833	0.573	0.56712
dat1\$South.America	20.6332	9.5239	2.166	0.03111 *
dat1\$Europe	5.0796	9.5101	0.534	0.59367
dat1\$Africa	6.4000	9.6010	0.667	0.50558

```
dat1$Oceania      2.3336   9.6849  0.241 0.80977
dat1$ofpopulationaged55.59 -1.4806   0.4696 -3.153 0.00179 **
```

```
---
```

```
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Residual standard error: 9.389 on 282 degrees of freedom
Multiple R-squared: 0.3252,   Adjusted R-squared: 0.3085
F-statistic: 19.42 on 7 and 282 DF, p-value: < 2.2e-16
```

```
>
```

```
> fiteiu16<-lm(dat1$Murder~dat1$Asia + dat1$North.America +
dat1$South.America + dat1$Europe +dat1$Africa + dat1$Oceania +
dat1$ofpopulationaged60.64)
> summary(fiteiu16)
```

```
Call:
```

```
lm(formula = dat1$Murder ~ dat1$Asia + dat1$North.America +
dat1$South.America +
  dat1$Europe + dat1$Africa + dat1$Oceania + dat1$ofpopulationaged60.64)
```

```
Residuals:
```

```
   Min     1Q   Median     3Q      Max
-20.365 -3.319 -1.813  0.708 38.776
```

```
Coefficients:
```

```
              Estimate Std. Error t value Pr(>|t|)
(Intercept)      7.8518   9.4746   0.829  0.4080
dat1$Asia         2.7513   9.4640   0.291  0.7715
dat1$North.America  5.3814   9.6572   0.557  0.5778
dat1$South.America 20.5856   9.5053   2.166  0.0312 *
dat1$Europe       5.3020   9.4924   0.559  0.5769
dat1$Africa       6.2676   9.5834   0.654  0.5136
dat1$Oceania      2.2346   9.6622   0.231  0.8173
dat1$ofpopulationaged60.64 -1.7892   0.5381 -3.325  0.0010 **
```

```
---
```

```
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Residual standard error: 9.371 on 282 degrees of freedom
Multiple R-squared: 0.3278,   Adjusted R-squared: 0.3111
F-statistic: 19.64 on 7 and 282 DF, p-value: < 2.2e-16
```

```
Call:
```

```
lm(formula = dat1$Murder ~ dat1$Asia + dat1$North.America +
dat1$South.America +
```

```
dat1$Europe + dat1$Africa + dat1$Oceania + dat1$ofpopulationaged65.69)
```

Residuals:

```
Min    1Q  Median    3Q   Max
-19.948 -3.456 -2.182 -0.033 39.935
```

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	5.617	9.590	0.586	0.5585
dat1\$Asia	2.351	9.599	0.245	0.8067
dat1\$North.America	4.056	9.779	0.415	0.6786
dat1\$South.America	20.233	9.633	2.100	0.0366 *
dat1\$Europe	3.788	9.653	0.392	0.6950
dat1\$Africa	6.479	9.714	0.667	0.5053
dat1\$Oceania	1.144	9.787	0.117	0.9070
dat1\$ofpopulationaged65.69	-1.151	0.633	-1.818	0.0701 .

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 9.497 on 282 degrees of freedom

Multiple R-squared: 0.3095, Adjusted R-squared: 0.2924

F-statistic: 18.06 on 7 and 282 DF, p-value: < 2.2e-16

Call:

```
lm(formula = dat1$Murder ~ dat1$Asia + dat1$North.America +
  dat1$South.America +
  dat1$Europe + dat1$Africa + dat1$Oceania + dat1$ofpopulationaged70.74)
```

Residuals:

```
Min    1Q  Median    3Q   Max
-19.974 -3.407 -2.067  0.208 40.374
```

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	4.7721	9.5722	0.499	0.6185
dat1\$Asia	2.1531	9.6159	0.224	0.8230
dat1\$North.America	4.0428	9.8068	0.412	0.6805
dat1\$South.America	20.2694	9.6514	2.100	0.0366 *
dat1\$Europe	3.4802	9.6898	0.359	0.7197
dat1\$Africa	6.6514	9.7302	0.684	0.4948
dat1\$Oceania	1.0146	9.8063	0.103	0.9177
dat1\$ofpopulationaged70.74	-1.0480	0.6982	-1.501	0.1345

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 9.515 on 282 degrees of freedom

Multiple R-squared: 0.307, Adjusted R-squared: 0.2898

F-statistic: 17.84 on 7 and 282 DF, p-value: < 2.2e-16

>

```
> fiteiu19<-lm(dat1$Murder~dat1$Asia + dat1$North.America +
dat1$South.America + dat1$Europe +dat1$Africa + dat1$Oceania +
dat1$ofpopulationaged75.79)
```

```
> summary(fiteiu19)
```

Call:

```
lm(formula = dat1$Murder ~ dat1$Asia + dat1$North.America +
dat1$South.America +
  dat1$Europe + dat1$Africa + dat1$Oceania + dat1$ofpopulationaged75.79)
```

Residuals:

Min	1Q	Median	3Q	Max
-20.078	-3.252	-2.244	0.399	40.053

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	4.2350	9.5543	0.443	0.6579
dat1\$Asia	1.9651	9.6200	0.204	0.8383
dat1\$North.America	4.0511	9.8239	0.412	0.6804
dat1\$South.America	20.2749	9.6599	2.099	0.0367 *
dat1\$Europe	3.2416	9.7026	0.334	0.7386
dat1\$Africa	6.6688	9.7385	0.685	0.4940
dat1\$Oceania	1.1077	9.8233	0.113	0.9103
dat1\$ofpopulationaged75.79	-1.0350	0.7762	-1.333	0.1835

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 9.523 on 282 degrees of freedom

Multiple R-squared: 0.3058, Adjusted R-squared: 0.2886

F-statistic: 17.75 on 7 and 282 DF, p-value: < 2.2e-16

```
lm(formula = dat1$Murder ~ dat1$Asia + dat1$North.America +
dat1$South.America +
  dat1$Europe + dat1$Africa + dat1$Oceania + dat1$ofpopulationaged80.84)
```

Residuals:

Min	1Q	Median	3Q	Max
-----	----	--------	----	-----

-20.036 -3.191 -2.091 0.395 40.233

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	4.1117	9.4888	0.433	0.6651
dat1\$Asia	1.9421	9.5679	0.203	0.8393
dat1\$North.America	4.7103	9.7781	0.482	0.6304
dat1\$South.America	20.3363	9.6146	2.115	0.0353 *
dat1\$Europe	3.9139	9.6128	0.407	0.6842
dat1\$Africa	6.6695	9.6926	0.688	0.4920
dat1\$Oceania	1.7161	9.7810	0.175	0.8608
dat1\$ofpopulationaged80.84	-1.8234	0.8683	-2.100	0.0366 *

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 9.479 on 282 degrees of freedom
Multiple R-squared: 0.3122, Adjusted R-squared: 0.2951
F-statistic: 18.28 on 7 and 282 DF, p-value: < 2.2e-16

Call:

```
lm(formula = dat1$Murder ~ dat1$Asia + dat1$North.America +
    dat1$South.America +
    dat1$Europe + dat1$Africa + dat1$Oceania + carsper1000)
```

Residuals:

Min	1Q	Median	3Q	Max
-18.372	-3.014	-2.020	0.230	40.005

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	3.380504	9.066117	0.373	0.7095
dat1\$Asia	1.994119	9.152421	0.218	0.8277
dat1\$North.America	5.598334	9.409099	0.595	0.5523
dat1\$South.America	18.673142	9.213566	2.027	0.0437 *
dat1\$Europe	3.604861	9.185686	0.392	0.6950
dat1\$Africa	9.266695	9.314840	0.995	0.3207
dat1\$Oceania	2.857173	9.419474	0.303	0.7619
carsper1000	-0.007521	0.003672	-2.048	0.0415 *

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 9.066 on 273 degrees of freedom
(9 observations deleted due to missingness)

Multiple R-squared: 0.285, Adjusted R-squared: 0.2666
F-statistic: 15.54 on 7 and 273 DF, p-value: < 2.2e-16

Call:

```
lm(formula = dat1$Murder ~ dat1$Asia + dat1$North.America +
  dat1$South.America +
  dat1$Europe + dat1$Africa + dat1$Oceania + petrol)
```

Residuals:

Min	1Q	Median	3Q	Max
-23.787	-4.408	-1.191	0.810	37.136

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-3.981141	9.500003	-0.419	0.675486
dat1\$Asia	3.983400	9.422022	0.423	0.672781
dat1\$North.America	5.697233	9.596992	0.594	0.553224
dat1\$South.America	24.007882	9.503078	2.526	0.012074 *
dat1\$Europe	5.097505	9.407130	0.542	0.588331
dat1\$Africa	9.604581	9.548400	1.006	0.315334
dat1\$Oceania	5.126779	9.669803	0.530	0.596401
petrol	0.035906	0.009371	3.832	0.000157 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 9.313 on 282 degrees of freedom
Multiple R-squared: 0.336, Adjusted R-squared: 0.3195
F-statistic: 20.39 on 7 and 282 DF, p-value: < 2.2e-16

Call:

```
lm(formula = dat1$Murder ~ dat1$Asia + dat1$North.America +
  dat1$South.America +
  dat1$Europe + dat1$Africa + dat1$Oceania +
  dat1$Workingagepopulationgrowth..pa.)
```

Residuals:

Min	1Q	Median	3Q	Max
-20.233	-3.472	-2.184	-0.172	38.155

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	0.5139	9.6457	0.053	0.9575

```

dat1$Asia          2.2992  9.6104  0.239  0.8111
dat1$North.America  3.9045  9.7878  0.399  0.6903
dat1$South.America 20.5331  9.6472  2.128  0.0342 *
dat1$Europe        3.1145  9.6262  0.324  0.7465
dat1$Africa        6.6740  9.7218  0.686  0.4930
dat1$Oceania       0.6779  9.7872  0.069  0.9448
dat1$Workingagepopulationgrowth..pa. 1.2210  0.7408  1.648  0.1004

```

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 9.507 on 282 degrees of freedom
Multiple R-squared: 0.3081, Adjusted R-squared: 0.2909
F-statistic: 17.94 on 7 and 282 DF, p-value: < 2.2e-16

Call:

```

lm(formula = dat1$Murder ~ dat1$Asia + dat1$North.America +
  dat1$South.America +
  dat1$Europe + dat1$Africa + dat1$Oceania + Employmentgrowth +
  petrol)

```

Residuals:

```

  Min    1Q  Median    3Q   Max
-24.364 -4.631 -1.071  1.006 37.131

```

Coefficients:

```

              Estimate Std. Error t value Pr(>|t|)
(Intercept)   -4.481259  9.538924  -0.470  0.6389
dat1$Asia      4.078424  9.397365   0.434  0.6646
dat1$North.America 5.777838  9.581650   0.603  0.5470
dat1$South.America 24.371347  9.452654   2.578  0.0105 *
dat1$Europe    5.319540  9.399749   0.566  0.5719
dat1$Africa    13.837099  9.581905   1.444  0.1499
dat1$Oceania    5.547524  9.630788   0.576  0.5651
Employmentgrowth -0.083719  0.298351  -0.281  0.7792
petrol         0.040374  0.009408  4.291 2.46e-05 ***

```

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 9.252 on 275 degrees of freedom
(6 observations deleted due to missingness)
Multiple R-squared: 0.3577, Adjusted R-squared: 0.339
F-statistic: 19.14 on 8 and 275 DF, p-value: < 2.2e-16

Call:

```
lm(formula = dat1$Murder ~ dat1$Asia + dat1$North.America +
  dat1$South.America +
  dat1$Europe + dat1$Africa + dat1$Oceania + dat1$Productivityofcapital.ICOR.)
```

Residuals:

```
Min    1Q  Median    3Q   Max
-19.697 -3.509 -2.390  1.282 39.424
```

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	4.12125	9.58402	0.430	0.6675
dat1\$Asia	1.07178	9.62464	0.111	0.9114
dat1\$North.America	2.37967	9.81100	0.243	0.8085
dat1\$South.America	19.63121	9.67968	2.028	0.0435 *
dat1\$Europe	0.59819	9.57972	0.062	0.9503
dat1\$Africa	7.67093	9.78200	0.784	0.4336
dat1\$Oceania	-0.09693	9.81752	-0.010	0.9921
dat1\$Productivityofcapital.ICOR.	-0.03144	0.03243	-0.970	0.3331

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 9.537 on 282 degrees of freedom

Multiple R-squared: 0.3037, Adjusted R-squared: 0.2865

F-statistic: 17.58 on 7 and 282 DF, p-value: < 2.2e-16

Call:

```
lm(formula = dat1$Murder ~ dat1$Asia + dat1$North.America +
  dat1$South.America +
  dat1$Europe + dat1$Africa + dat1$Oceania + dat1$ofpopulationaged20.24 +
  dat1$ofpopulationaged15.19 + dat1$Female.ofpopulation)
```

Residuals:

```
Min    1Q  Median    3Q   Max
-20.642 -3.766 -1.644  0.157 39.292
```

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	23.3797	25.6366	0.912	0.3626
dat1\$Asia	1.9392	9.5117	0.204	0.8386
dat1\$North.America	5.3019	9.7080	0.546	0.5854
dat1\$South.America	20.4479	9.5490	2.141	0.0331 *
dat1\$Europe	4.2732	9.5432	0.448	0.6547


```

dat1$Africa      4.6245  9.6384  0.480  0.6317
dat1$Oceania     1.1471  9.6998  0.118  0.9059
dat1$ofpopulationaged20.24 2.2350  1.0166  2.199  0.0287 *
dat1$ofpopulationaged15.19 -0.7344  0.8322 -0.883  0.3783
dat1$Female.ofpopulation -0.6640  0.4713 -1.409  0.1600

```

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 9.401 on 280 degrees of freedom
Multiple R-squared: 0.3282, Adjusted R-squared: 0.3066
F-statistic: 15.2 on 9 and 280 DF, p-value: < 2.2e-16

Call:

```
lm(formula = dat1$Murder ~ dat1$South.America + dat1$ofpopulationaged20.24 +
    dat1$ofpopulationaged15.19 + dat1$Female.ofpopulation)
```

Residuals:

```

      Min       1Q   Median       3Q      Max
-20.442  -3.683  -1.795  -0.161   39.168

```

Coefficients:

```

              Estimate Std. Error t value Pr(>|t|)
(Intercept)    19.1690    22.6583   0.846   0.398
dat1$South.America    16.9701     1.7654  9.613 <2e-16 ***
dat1$ofpopulationaged20.24  2.0687     0.9924  2.085  0.038 *
dat1$ofpopulationaged15.19 -0.6894     0.8141 -0.847  0.398
dat1$Female.ofpopulation -0.4906     0.4300 -1.141  0.255

```

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 9.389 on 285 degrees of freedom
Multiple R-squared: 0.318, Adjusted R-squared: 0.3085
F-statistic: 33.23 on 4 and 285 DF, p-value: < 2.2e-16

Call:

```
lm(formula = dat1$Murder ~ dat1$South.America + dat1$ofpopulationaged20.24 +
    dat1$Female.ofpopulation + petrol)
```

Residuals:

```

      Min       1Q   Median       3Q      Max
-24.073  -3.757  -1.370   1.290   37.767

```

Coefficients:

```

              Estimate Std. Error t value Pr(>|t|)

```

```

(Intercept)          9.399164 21.147676 0.444 0.657052
dat1$South.America    17.325886 1.717387 10.089 < 2e-16 ***
dat1$ofpopulationaged20.24 1.131191 0.396684 2.852 0.004668 **
dat1$Female.ofpopulation -0.324025 0.394505 -0.821 0.412137
petrol                0.032490 0.008805 3.690 0.000268 ***

```

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 9.184 on 285 degrees of freedom

Multiple R-squared: 0.3475, Adjusted R-squared: 0.3383

F-statistic: 37.94 on 4 and 285 DF, p-value: < 2.2e-16

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“Many writers claim that nearly all crime is caused by economic conditions, or in other words that poverty is practically the whole cause of crime. Endless statistics have been gathered on this subject which seem to show conclusively that property crimes are largely the result of the unequal distribution of wealth. But crime of any class cannot be safely ascribed to a single cause. Life is too complex, heredity is too variant and imperfect, too many separate things contribute to human behavior, to make it possible to trace all actions to a single cause.

CLARENCE DARROW, *Crime: Its Cause and Treatment*